Production Process Moves and the Effective Management of Process Knowledge

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Dedication

I dedicate this to my parents, Jesse and Ethel Kent. Even though you are no longer here, I wouldn't be where I am without the love, dedication and passion you always showed me. I also dedicate this to my son, Nolan Kent. I love you dearly and strive to always make you proud!

Abstract

While production process moves are more prevalent than ever, there have mostly been studies that look at the "what", "why", and "where" of a move (Chen et al. 2015; Cohen et al. 2016; Wu and Zhang 2014; Simchi – Levi 2012; Sirkin et al. 2014). Little research examines the "how" of a move. After a firm decides to move their production process, *how* do they do it in a way that will minimize downtime and allow them to achieve their pre-move performance quickly? Based on in depth discussions with multinational companies who have undergone production moves, my dissertation focuses on the transfer of production knowledge. Specifically, the dissertation is organized into three essays.

The first essay focuses on ***template use*** and its link to performance. A template can be described as a working example of organizational routines that contains both critical and noncritical elements of the routines (Nelson and Winter, 1982). Using behavioral experiments in which 4-person teams put together complex building devices, I demonstrate that template use leads to improved performance vs. not using templates at all. However, I also show that strict template use, without the ability for teams to adjust the process, leads to reduced performance.

Building on the results of the first essay, the second investigates the role of ***functional diversity*** in enhancing/eroding knowledge transfer effectiveness when using templates. Functional diversity is defined as the extent to which education, experience and expertise of team members across different teams vary (Jehn, 1999). Through the creation of an experiment in which I have production knowledge being transferred between subjects with either a Business or Engineering background, I find the results to be contextual. When transferring the process from Business to Engineering, functional diversity leads to reduced performance, likely due to a lack of credibility given to the Business teams by the Engineers. However, when knowledge is transferred from the Engineers to Business teams, functional diversity performance is in line with "within function" results.

Lastly, the third essay looks at the role that ***national culture*** plays in a firm's ability to transfer knowledge between countries that have unique cultures. I create an experiment that involves knowledge transfer within and between teams located in two important, yet unique countries: United States and China. I also examine if collocating members of the source team with the recipient team members mitigates the impact of national culture. The results show that transferring knowledge between unique cultures leads to reduced performance vs. transferring knowledge within similar cultures. In addition, colocation is a successful strategy to employ for the Chinese recipient teams, while it has no effect on U.S. team performance.

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Chapter 1

Dissertation Overview

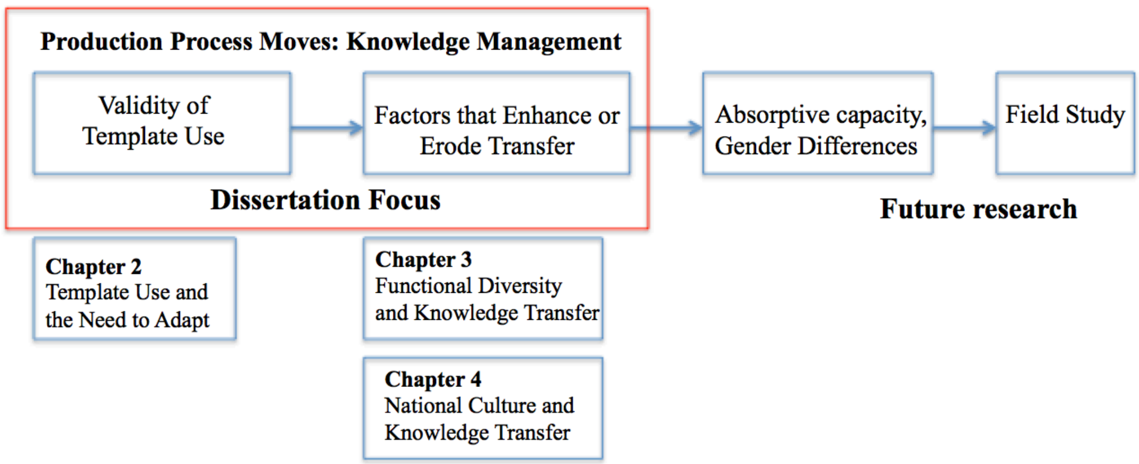
Changing customer demand, increasing production costs, and emerging growth opportunities often generate pressure on firms to relocate their production processes. Although it would be ideal if manufacturing plants were be built on barges so that they could be moved from place to place quickly and without resistance, moving a process is a disruptive affair that involves learning and adaptation. Every process move risks an insufficient pace of learning and an incomplete adaptation of the process to local environments. The pressure to move a process in response to a changing economic landscape must be clearly weighed against the disruption and risk such a move implies to the firm's own processes and to the value chain the firm is embedded in. Further, actively managing this disruption by effectively transferring knowledge between a source and recipient site is clearly an important task for operations managers.

There are many examples of firms choosing to move production to improve their competitive position. In the 1990s, firms such as Apple, Hewlett Packard, Procter and Gamble all moved production of key products to contract manufacturers in China to take advantage of low labor costs in the area. More recently, General Electric made the decision to move production of turbines and generators from the U.S. to Europe and China, in order to secure the necessary export financing required by their customers (GE press release, September 15, 2015). Numerous reports, including those done by the Boston Consulting Group (2012), MIT (2012), Chen et al. (2015) and Cohen et al. (2016) show that many firms are actively moving their processes or seriously considering a move, indicating that production process moves remain a current and frequent phenomenon (The Economist, January 2013).

While process moves continue to happen, there is little research in the field of operations management examining this phenomenon. Within my dissertation, I study production process moves and knowledge management – creation, transfer and retention -

via behavioral laboratory experiments. Behavioral experiments allow me to better examine causality when looking for the link between the various independent and dependent variables. Experiments by themselves do not prove theory, but coupled with field studies and other research, experiments can strengthen/weaken the confidence we have in the existing theory (Siemsen, 2011). My research addresses the following question: What factors impact performance during/after a production move and how can firms effectively transfer process knowledge?

Figure 1.1 Dissertation Structure



In chapter two, "*Production Process Moves: Template Use and the Need to Adapt*", I begin my investigation of production process moves by studying template use as a way in which firms may effectively be able to create, transfer and retain knowledge. The merits of template use have been discussed within the strategic management literature over the last few decades (Winter & Szulanski, 2001; Jensen and Szulanski 2007; Szulanski and Jensen 2008). These papers demonstrate that there is value in using templates. However, they gather data in a services context within a fairly stable environment. In my study, I focus on template use in a *production* context, and I introduce product change, because many firms use a process move as an opportunity to also make scheduled changes to their product. Ultimately, I conducted two studies. In the first study, the research question is: Does template use lead to higher performance when transferring production process knowledge? Through a series of experiments where 4 person teams worked together to build complex devices, I find that template use does lead to higher performance, especially when the source and recipient contexts are similar. Based on results from the first study, I conducted a second study to see if there were boundary conditions to the positive impact template use has on performance during a production process move. I asked the following question: <u>Does rigidly enforcing a template result in adverse behavioral consequences at the recipient site</u>? I find that rigidly enforcing a template reduces performance, likely due to the reduction in the sense of ownership and ultimately motivation on behalf of the production teams involved. Similar to the literature on motivation and empowerment (Bernstein 2012; Zhang and Barton 2010; Mathieu et al. 2006), I find that allowing production teams to play a role in crafting their work leads to desired results.

It is common within organizations for work to be done by workers in a team. Naturally, there has been much debate within firms as well as within the academic literature on how to structure these teams (Ancona and Caldwell, 1992). Should the team have members with similar or diverse functional backgrounds? The usual form of diversity discussed in the literature is *within* team diversity, because the work is usually being done within the same business unit/department/work group, regardless of whether the people are geographically close or far. But when considering a production process move, it may involve a transfer from one business unit to another, one subsidiary to another, or even from one company to another. Therefore, different teams are involved in the transfer. This context requires a discussion of ***between team*** diversity, rather than the typical discussion of within team diversity. My second essay, titled, "*Functional Diversity and its Impact on Knowledge Transfer Effectiveness*" addresses this gap by focusing on between team diversity and how it impacts performance. The research question is: <u>Does between team functional diversity impact the effectiveness of a proven template when transferring process knowledge?</u>

My first essay shows that template use leads to a higher learning rate during knowledge transfer. In my second essay, I want to better understand if functional diversity between the source and recipient teams will enhance, hinder or have no effect on transfer performance. I draw on several papers in past literature to help motivate my research and the past results are mixed regarding functional diversity and its impact.

Ancona and Caldwell (1992) finds that functional diversity leads to increased communication between team members, however they find a negative overall effect of functional diversity. They find that that innovation increases but functional diversity "impedes implementation because there is less capability for teamwork than there is for homogenous teams." Conversely, Jehn et al. (1999) finds that while diversity leads to increased conflict between team members, it increases overall productivity. Sampson (2007) studies R&D collaborations, so it is one of the only papers that is interested in between team diversity. They argue for a low level of functional diversity and ultimately demonstrate that a moderate level works best.

In the second essay, through a series of experiments in which Business and Engineering school students are transferring production knowledge within and between their function, the results are contextual, similar to Sampson (2007). When knowledge is transferred from Business to Engineering, there is an initial performance reduction, likely due to a lack of credibility given to the Business teams by the Engineers. However, when knowledge is transferred from the Engineers to Business teams, functional diversity performance is in line with the "within function" results. Taken together, the results show that functional diversity is not a cure all for team related work, and that managers should employ this approach carefully.

While the role of national culture has been studied previously, there has been very little investigation into national culture and its impact on performance within a production environment. So in my third essay, titled "*National Culture and its Impact on Knowledge Transfer Effectiveness*", I investigate the following research questions: <u>1.) Does National Culture matter when moving a production process from one culture to another, and, 2.) If National Culture matters, what strategies can be implemented by managers to neutralize these effects?</u> There are several studies (Bhagat et al. 2002; Javidan et al. 2005; Ozer et al. 2014; Hofstede 1980, 2010) from the past that look at national culture and how it may impact knowledge transfer/sharing that guide my research in this area. Bhagat et al. (2002) offers a number of theoretical propositions, arguing that individualist (e.g. U.S.) cultures value *explicit* knowledge, while collectivist cultures (e.g. China) value tacit knowledge. They also argue that knowledge will move faster within culture than in cross culture transfers. Javidan et. al. (2005), through the explanation of a cross cultural case study, demonstrate the difficulty in moving knowledge across cultures. They argue that knowledge transfer within culture is difficult enough, so when an extra layer of difficulty is introduced, that makes it much harder to do successfully. Their advice is that executives should take a "proactive and systematic approach to dealing with cultural differences". In Ozer et al. 2014, the authors, through experiments between Chinese and U.S. students, find cultural differences in how each culture exhibits trust and shares information. They argue that the lack of trust the Chinese subjects show is due to their cultural upbringing. Hofstede (1980, 2010) spent years (1967-1973) gathering data from IBM employees across 70 countries. Through this research, he proposed several dimensions (*individualism/collectivism, power distance, masculinity, and uncertainty avoidance)* that help explain the similarities and differences among people from different countries.

Within the third essay, through a series of experiments in the United States as well as in Shanghai, China, I find that national culture **does** matter. The cross-cultural knowledge transfer performance is lower than within culture performance. I also find that U.S. teams perform better than their Chinese counterparts, which is what we would expect based on the propositions from Bhagat et al. (2002) regarding how individualists value explicit knowledge more than collectivist. I also find that collocating a member of the source team with the Chinese recipient teams leads to far better performance than when collocation is not present. This is also consistent with Bhagat et al.'s theory on the value collectivists place on tacit knowledge. Taken together, the results from this essay show that national culture must be considered when firms are transferring production knowledge within and between cultures.

Collectively, this dissertation provides a comprehensive investigation of knowledge creation, transfer and retention and how firms can create strategy to increase the chances of a successful production process move. The goal of this research is to deepen the understanding of production process moves so that firms engaged in them can create winning strategies. In addition, this research will help form a foundation that future researchers can build upon when they are investigating the "*how*" of a move. I empirically demonstrate factors that lead to knowledge transfer effectiveness, as well as factors that may impede a firm's ability to transfer vital production knowledge.

Chapter 2:

Production Process Moves: Template Use and the Need to Adapt

2.1. Introduction

Changing customer demand, increasing production costs, and emerging growth opportunities often generate pressure on firms to relocate their production processes. Although it would be ideal if manufacturing plants could be relocated quickly and easily, moving a process is disruptive and involves coping with a new learning curve to ramp-up production. Every process move risks an insufficient pace of learning and an incomplete adaptation of the process to the local environment. The pressure to relocate in response to a changing economic landscape must be weighed against the disruption and risk to the firm's own processes and to the value chain in which the firm is embedded. Further, actively managing this disruption by effectively transferring knowledge between a source and recipient site is an important task for operations managers.

Consider the example of Mabuchi Motors. The company approached one of its major customers, Procter & Gamble (P&G), about moving its production of motors for two of P&G's major Swiffer products from China to Vietnam. The decision to move the process was made in response to increasing production costs in China. P&G objected to the move because both product lines were in a growth phase, and P&G management did not want to risk any manufacturing disruptions. However, Mabuchi was the sole supplier of these specific motors to P&G. As a result, P&G had little leverage in the subsequent negotiations. Mabuchi projected that it would take six months to begin production in Vietnam, an estimate that encompassed closing Chinese operations, moving the equipment, and recruiting and training a new workforce in Vietnam. However, after 12 months — six months past the originally scheduled start-up — Mabuchi was still encountering high defect and scrap rates on the Vietnam motor line. The consequent lack of motors was beginning to threaten P&G's ability to deliver the finished products. Ultimately, although Mabuchi had produced the motors in China for more than 10 years without problems, the company was unable to effectively transfer this capability to Vietnam. The failure of this relocation of production was in large part due to Mabuchi underestimating the difficulty of capturing knowledge at the source location and transferring it to the recipient site. The company also underestimated the costs and planning necessary for the proper implementation of the production process at the recipient facility (see e.g. Gaimon et al. 2011). As a result, P&G executives were forced to qualify an alternate source for this component and eventually dropped Mabuchi as their supplier.

As this example highlights, the increasing production costs in China are currently a force driving the movement of production processes. Several U.S. companies with operations in China are either moving their production farther inland there, back to the United States or to Mexico, or to regions with still lower labor costs**.** In a survey of American manufacturing companies by the Boston Consulting Group (BCG) in 2012, 37% of firms with over $1 billion in annual sales and 48% of firms with over $10 billion in annual sales were planning to or were already in the middle of moving production from China back to the United States. The primary reason given for this shift was the dramatic increase in labor costs in China since 2000, an increase estimated at between 7.1% and 7.8% per year. Similar studies by the Massachusetts Institute of Technology (*The Economist*, January 2013) and Wharton (Chen et al. 2015; Cohen et al. 2016) found a great deal of production process movement in and out of China. The movement was driven by several reasons, including *proximity* to demand, *market changes,* and *innovation*, i.e., a desire to move manufacturing closer to a firm's research and development center (Gray et al. 2015, Cohen et al. 2016). Moving a process is not a rare and unusual event; rather it is a normal change affecting global supply chains.

Although these process moves occur regularly in practice, little research has been done in operations management (OM) to examine this phenomenon, especially *how* firms can achieve their desired process move outcomes. In our study, we apply a behavioral lens to this topic. Although production process moves are complex and multidimensional organizational events, at their core lies an exercise in effective knowledge management (creation, transfer, and retention) and task understanding. Both undertakings lend themselves to behavioral research. When psychologists first studied learning curves, they turned to laboratory experiments to gain a better understanding of the phenomenon (Ebbinghaus, 1885; Thorndike 1898; Thurstone 1919). Field studies later confirmed their findings (e.g., Wright, 1936; Hirch, 1952; Argote and Epple, 1990; Darr et al. 1995). We thus believe that using laboratory experiments is a useful point of departure for further OM research in this domain. Prior experimental research has also studied complex organizational phenomena, such as Weber and Camerer (2003), who examine the effect of culture on mergers and acquisitions with a series of laboratory experiments involving teams of three people.

A key aspect of process moves we study is whether the use of templates during a move can create more effective knowledge transfer. Nelson and Winter (1982) described a template as a working example of organizational routines that contains both critical and noncritical elements of the routines. These various elements "provide the details of how the work gets done, in what sequence and how various components and subroutines are interconnected" (Nelson and Winter 1982, pp. 119-120). In a real-world manufacturing context, Intel has become known for its Copy Exactly technology transfer method, which can be thought of as a very strict form of template use. Semiconductor manufacturing has very complex process flows with tight tolerances. The Copy Exactly method was developed to accelerate technology transfer while maintaining expected product quality and yields. The philosophy is that "everything which might affect the process, or how it is run is to be copied down to the finest details, unless it is either physically impossible to do so, or there is an overwhelming competitive benefit to introducing a change" (McDonald 1998, page 2).

Several papers in the strategic management literature have demonstrated that template use is an effective way to transfer knowledge and achieve desired results in the context of franchise replication (Darr et al. 1995, Winter and Szulanski 2001, Jensen and Szulanski 2007, Szulanski and Jensen 2008, Winter et al. 2012). The primary reason for studying this setting is that "franchise organizations provide a natural laboratory for the study of replication as they compete primarily through the creation and operations of a large number of very similar outlets according to a uniform business model" (Szulanski and Jensen, 2008, p. 1734); hence, little to no variation. This level of uniformity is counter to how we conceptualize production moves, because each production environment may vary greatly in terms of product/technology mix, labor skills, suppliers, and climate.

Although the strict use of templates for knowledge transfer has its supporters, template use has also been shown to ***restrict*** search, thereby prohibiting a knowledge recipient from effectively adapting new knowledge to the local environment (Victorino et al. 2013) or having rapidly diminishing returns in the new environment (Szulanski and Jensen, 2008). Do the advantages of template use outweigh the disadvantages? Not using a template, also referred to as local adaptation, may be an advantageous approach if recipients of the process require a clean slate to enable them to search for ways to adapt a process to a local environment.

Consider the example of West Pharmaceutical Services, Inc., a $1B+ manufacturer of rubber and plastic components. Its managers saw a need to deviate from an established template in moving a process from the United States to Mexico. West was supplying jars and closures for P&G's Vicks VapoRub brand. P&G's managers told West of their intention to move all of their major suppliers closer to their Naucalpan, Mexico, plant. West had been manufacturing its supplies for P&G in New Jersey, so this request meant moving production out of the country if West hoped to retain this current business with P&G. Essentially, West was faced with the Greenfield vs. Brownfield dilemma that many firms face when moving a process (Gaimon et al. 2017). Do they build a new facility from the ground up (Greenfield), which would enable them to design specifically for the intended use? Or do they upgrade/adapt an existing facility (Brownfield), which would take less time and allow them to leverage current employees? Since West already had a plant in Mexico (Cuernavaca) capable of just-in-time delivery of products with only a short lead-time, they employed a Brownfield approach. However, this plant lacked the technological capability to absorb a sophisticated injection blow molding process, and thus changes to the process were necessary.

To adapt the process to fit the skills and capabilities available at the facility in Mexico, West's managers put together a cross-functional team composed of key personnel (research and development, engineering, manufacturing, etc.), including managers from the Mexican facility. This team recommended that West should buy new equipment and molds instead of moving the old equipment, because the updated technology was more aligned with the new business requirements. However, instead of shipping the new equipment directly to Mexico, West's managers had the new equipment delivered to their technical headquarters in the United States. There, the cross-functional team, which had members with injection blow molding expertise, could qualify the process and train the personnel from Mexico who would be using the new equipment. This was an example of learning before doing vs. learning by doing (Sommer and Loch, 2004). Because of West's ability to thus adapt its established process template, the company could qualify the process in Mexico on time and at cost for its customer. This enabled West not only to keep its current business, but also to position itself for additional growth. The example highlights that simply replicating an existing template may often not be the right approach for a successful process transfer; changing environmental conditions may necessitate process adaptations.

Another consideration in the use of templates is their potential to erode the sense of ownership in the process at a recipient site. If a template is designed at the source and handed to the recipient without any opportunity for the recipient to influence the template, organizational resistance toward the template can arise quickly. Defects and inefficiencies will be blamed on the template, and the drive to root out such waste will be diminished. Employees involved will see their input as purely transactional; their motivation to excel in the process may suffer as a result. Rigid templates will ensure better knowledge transfer and standardization, but may also have behavioral consequences at the recipient site by lowering the intrinsic motivation to work and improve the process. To that point, Mathieu et al. (2006) and Zhang and Bartol, (2010) showed that psychological empowerment, which can be characterized as having a sense of perceived control, perceived competence, and internalization of the goals and objectives of the organization (Menon et al. 1999), leads to increased employee creativity, customer satisfaction, and quantitative performance. As Jaikumar and Bohn (1992) point out, within a *static* environment, it is assumed that all production technology is known and therefore, the only role of labor would be to simply execute the procedures specified by management. But firms today exist in a *dynamic* world in which production should be evolving and process improvement, with the help of those working in the production environment, should have high priority.

In summary, we pursue two research questions in our work. First, we ask whether and when templates lead to improved performance after a production process move, given that conditions at the source and recipient sites may not exactly match. Second, we ask whether rigidly enforcing a template results in adverse behavioral consequences at the recipient site. Our results from two behavioral experiments address these questions. Our first behavioral experiment involved 57 four-person teams, with each team working to assemble a device five times over. Some teams received a template for guidance, and some did not receive such a template. Further, some teams worked on exactly the product that the template was designed for, but others worked with the same template but on a slightly different product. In our second experiment, which involved an additional 30 four-person teams, all teams worked with a template they were not allowed to modify when building the product. Data from this experiment was compared with data from our first experiment in which teams could modify their process and deviate from the template after the experiment had started.

The remainder of the paper is organized as follows: In Section 2, we examine the relevant literature. In Section 3 we present Study I and provide the theory, experimental design, analysis and results. In Section 4, we present Study II, including theory, the experimental design, analysis and results. In Section 5, we conclude by highlighting the strategic and operational implications of this study, its limitations, and explore future research directions.

2.2 Literature Review

Organizational Learning and Learning Curves

Organizational learning theory is well developed, (see Argote, 2013 for a complete literature review) with contributions from numerous academic areas like organizational behavior, economics, strategy, psychology, and information systems. A complete review of this literature is beyond the scope of our work, but this stream of research contains several studies that deliver important insights for our current research context.

Argote et al. (1990) analyzed the persistence of learning in a manufacturing environment as well as the *transfer* of knowledge across production facilities within the same organization. Before their study, it was assumed that manufacturing costs continue to decrease at a decreasing rate as long as more volume (experience) is being made, irrespective of time. By using data from the builders of the World War II era Liberty ships, the authors found that learning depreciates rapidly if not replenished with a steady stream of volume. In fact, if continued production did not replenish the stock of knowledge available at the beginning of a year, at year's end only 3.2% of the knowledge would remain. They also showed that if volume drops by a significant amount (e.g., 50%), the cost or defect rate would increase before eventually decreasing again. This study also found that of the 16 active Liberty shipyards, those built later benefited from the knowledge accrued by the earlier ones, but this learning benefit depreciated rapidly. Analyzing a more detailed dataset on the Liberty ships construction collected from the U.S. National Archives, Thompson (2007) found that organizational forgetting is not quite as forceful as estimated by Argote et al. (1990), though still present in the data. Taken together, these findings highlight the difficulty of transferring knowledge between production environments, even when they are very similar, as well as how difficult it can be to *retain* knowledge (de Holan and Phillips 2004; Argote et al. 2003).

Epple et al. (1991) examined the hypothesis that acquired knowledge can be 100% contained in technology. They analyzed this question by gathering data on knowledge transfer across shifts in a plant, the idea being that if knowledge can be completely captured with technology, its transfer across shifts should be complete because the shifts both use the same technology. Using data from a large North American truck plant, the authors found that although much of the knowledge was transferred via technology in the expansion of production from one to two shifts, knowledge transfer remained incomplete. This rejects the hypothesis that technology can fully capture operational knowledge. A large investment in training was made before moving to two shifts; this investment in the plant workers was vital to a successful transfer of knowledge from one shift to two. When compared with Argote et al. (1990), these results suggest that intra-plant transfer of knowledge is easier than the transfer between production facilities that are geographically separate (Epple et al. 1991). This finding alludes to the "stickiness" of knowledge — that is, the difficulty of moving knowledge in and between organizations (von Hippel, 1994; Szulanski 2002).

Lapre and van Wassenhove (2001) analyzed organizational learning by studying knowledge transfer data from Bekaert, a multinational steel corporation. Bekaert's managers wanted to induce increased learning at multiple locations by replicating a high performing production line (Model Line A or MLA). They created three additional lines, MLB, MLC1, and MLC2, but could not match the results found with MLA. The authors concluded that a learning rate is not a given constant but a dependent variable largely influenced by management. With the three replicated lines, Bekaert's managers failed to provide the necessary amount of experience, expertise, and focus when they assigned people to the replicated lines. It was this failure that led to reduced performance (total factor productivity) in moving from MLA to MLB, MLC1, and MLC2.

Template Use in Knowledge Transfer

Several studies in the fields of strategy show that template use can lead to successful knowledge transfer (Winter and Szulanski 2001, Jiang et al. 2004, Jensen and Szulanski 2007, Szulanski and Jensen 2008, Winter et al. 2012). For example, in Winter & Szulanski (2001), the authors expressed a need for firms' managers to think more strategically when seeking to expand via replication. They argued that managers at many firms, as well as organizational theorists, think of replication as simply a reapplication of a known formula and underestimate the difficulty they face when seeking to add locations. They articulated a theory that in their view recognizes managers' effort to create a business model to transfer, all the while dealing with the issues that crop up during knowledge transfer. Ultimately, they proposed the strict use of templates to ensure that the knowledge transfer portion of replication is successful. They asserted that "when guided by a template, the exploitation of a business model by replication is more effective and profitable when replication tactics rely on an initial effort to copy the template precisely” (Winter and Szulanski 2001, page 737).

In Jensen and Szulanski (2007), the authors’ goal was to empirically study the claim that template use enhances performance during knowledge transfer. They conducted an eight-year case study that included a repeated quasi-experiment within Xerox Europe. On three separate occasions, the company’s managers had wanted to transfer sets of best practices to its sales force. The authors studied template use as their independent variable; their dependent variables were adoption and performance (sales force productivity, ratio of selling costs to revenue, etc.). Their key result was that in two cases (Wave I and Wave III), there was a high adoption of the prescribed template, and the results after implementation far exceeded initial expectations. Wave II did not use a template, and adoption of best practices was low (40%) and deemed a failure. The authors concluded that template use and knowledge transfer effectiveness are positively correlated.

Although these past studies demonstrate that template use leads to better performance, they differ from our current study along several dimensions. First, apart from the two studies that focus on Intel (McDonald 1998; Terwiesch and Xu 2004), previous studies have predominantly examined service and not manufacturing environments. Although the results from these studies may apply in a manufacturing environment as well, testing the use of templates in the production of products could yield different results. While service environments are characterized by heterogeneity – i.e. individual units of production being unique (Sampson and Froehle 2006) – manufacturing environments tend to have more standardized outputs, and they are therefore more amenable to a precise set of specifications. Further, service processes usually involve direct interaction with customers, whereas manufacturing contexts are removed from customers. This creates less opportunity for variation in the process, but also provides only delayed feedback as to how decisions made in the production process impact customers. In turn, these differences between manufacturing and service environments may lead to templates affecting employee behavior differently in manufacturing than in services.

Second, the level of analysis in previous research was at the *firm* or *store unit* level, but our study analyzes performance at the *team* level. This distinction is significant because when studying the merits of a practice like template use, it is important to get close to where the work is being done. In manufacturing, this occurs at the team level. Once we understand operations at the team level, we can better assess if the practice being used is effective. Then we can make educated assumptions about what that means at higher levels (shift, plant, and firm). If we begin by studying the broader levels, as past studies have done, we could miss valuable insights that tend to emerge only closer to the point of execution.

Third, past studies have focused on templates in a very dichotomous way – either templates were or were not used. In contrast, our experiments are finer grained because they add a temporal dimension to the rigidity of the template: In our first experiment, templates must be used initially and can be altered afterward. Our second experiment enforces the rigid use of the template throughout the whole experiment. This allows us to test whether there is a difference between providing the template merely as an initial suggestion to transfer knowledge or as a rigid tool for process standardization instead.

Lastly, we are looking at the role of template use in conditions of both high and minimal changes in environments (see next section). This is salient because the previously mentioned studies looked at template use in a familiar environment, noting that franchise organizations provide a natural laboratory for the study of replication because they compete primarily through the creation and operation of many very <u>similar</u> outlets (Winter et al. 2012, p. 674). Appropriate to that point, Victorino et al. (2013) empirically showed in an individual service task (service scripting in hotels) that in a state of high change, template use leads to lower performance; we wanted to examine if this reduced effectiveness of templates holds true in the setting of a manufacturing team as well.

<u>Environmental and Technological Change</u>

Production moves are unique because although there may be an implied *expansion* of business, they largely involve moving *current* business, which is riskier than growing through replication/expansion; be it new shipyards (Argote et al 1990), increased numbers of manufacturing lines (Lapré and Wassenhove 2001), or new small office/home office stores (Szulanski and Jensen, 2008; Winter et al. 2012). Viewed from this perspective, it is crucial to execute a process move well; if not, the existing business is at risk, and there is little redundancy that may mitigate this risk in case of unexpected challenges. In addition, a move often means organizational change in which the people originally responsible for a process are no longer managing the process after the move (and they possibly lose their jobs). Some form of external pressure (e.g., competitive response, governmental mandates, and customer requests) typically drives a decision to change. Thus, a process move implies some form of environmental change and adaptation.

We view change as an important factor to study for several reasons. First, no company operates in a static environment; a consistent need for change is always present because of government regulations, competition, consumer preferences, etc. Secondly, as the West Pharma example demonstrates, many companies regard a process move as an opportunity to change the product and/or process itself, either because it is time to do so in the product's lifecycle or for strategic reasons (e.g., cost, consumer preferences, customer mandate, competitive response). Further, the new location may require changing suppliers (because of transportation costs or local content rules) or the technology itself (e.g., because of differences in barometric pressure). Lastly, it has been demonstrated that implementing process change, if coupled with preparation and training (and template use is a specific form of training), can lead to long-term revenue growth via reduced unit cost and/or premium product price (Carrillo and Gaimon, 2000). Our goal is to examine if environmental change affects the effectiveness of a template in the transfer of knowledge from a source to a recipient.

2.3. Study 1 – The Effect of Using a Template

The focus of our first study was to analyze the impact of using a template when transferring knowledge within both low- and high-change environments. Four-person teams must assemble a device five times over. Some teams received a template, and some did not. All teams could adjust their production process between rounds.

2.3.1 Theory

Previously, the use of templates during knowledge transfer had been primarily studied in the field of strategy. Szulanski and Jensen (2008) examined the merits of template use in a low change setting, as it related to franchisor network growth in new countries. They gathered panel data from one U.S-based firm (Mailboxes, Etc.), which sells master licenses to outside companies; this has resulted in franchise networks in 23 countries. The researchers' goal was to address two questions: "to what extent is such a strategy of 'copying more exactly' efficacious in the cross-border transfer of knowledge; and if such a positive effect exists, how persistent is it?" Using network growth as the dependent variable and copying more exactly as the independent variable, they did not find support for their hypothesis favoring local adaptation. However, they did find support for a hypothesis favoring a copy more exactly strategy as well as support for an assertion that following this strategy has a diminishing impact over time. These findings, which are consistent with other literature in this domain, suggest that knowledge transferred precisely from headquarters may be more valuable than wisdom that comes from local units and that introducing innovation may cause abandonment of the knowledge that made the franchise successful in the first place. This knowledge from the source leads to higher initial performance, although the authors argue that the impact of the transferred knowledge wanes over time.

A different stream of research looks at mental models and their impact on team performance. Mental models can be defined as a "mechanism whereby humans generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of future system states" (Rouse and Morris 1986, p. 360). These models allow people to *describe*, *explain,* and *predict* events in their environment (Mathieu et al. 2000). Converse (1993) suggests that when individuals are put in a team environment, they draw on common or shared mental models to effectively complete tasks. When the tasks are complex, multiple mental models must be shared among team members to achieve desired performance (Mathieu et al. 2000). These mental models include (1) technology/equipment models, where team members must understand how the various forms of technology/equipment interacts with each other, (2) job/task models**,** in which knowledge is organized related to how the task is accomplished through procedures and contingencies, (3) team interaction models that "describe the roles and responsibilities of team members, interaction patterns, information flow, role interdependencies and information sources" (Mathieu et al. 2000, page 274) and (4) the team Member model, which helps outline the strengths, weaknesses, tendencies and knowledge of the various teams members and it allows them to "tailor their behavior in accordance with that they expect their teammates to do" (Mathieu et al. 2000, page 274). These four mental models can be broadly defined in two primary content areas: *task-related* features of the situation (e.g., technology/equipment and job/task models) and *team-related* elements of the situation (e.g., team interaction and team models). Mathieu et al. (2000) empirically shows that the existence of these mental models leads to improved team performance. If we look at the creation of shared mental models through an Input-Process-Outcome framework (Gladstein, 1984; Guzzo and Dickson, 1996, Mathieu et al. 2000), a well-established template serves as a key *input* to the creation of a shared mental model that teams can then use to deliver increased performance (Heffner et al. 1995; Volpe et al. 1996).

Taken together, these studies demonstrate that when it comes to production moves being made in a low-change environment, it does not make sense to deviate from a proven template. Further, teams that have knowledge that allows them to describe, explain, and predict events in their environment will work together more effectively and deliver better performance. Therefore, we submit our first hypothesis:

> HYPOTHESIS 1A***:*** *Under low product/process change, template use leads to higher initial performance (faster learning) after knowledge transfer, vs. local adaptation of the process.*

H1A suggests there are initial performance advantages associated with using a template. But do these performance advantages persist or even increase over time? To examine this question, Winter et al. (2012) used longitudinal data from the same company studied in Szulanski and Jensen (2008) and examined the "outlet specific risk of failure." The independent variable of interest was a franchise outlet's deviation from the franchisor template. The study's findings suggest that certain types of deviation from the template (the sale of nonstandard products in this sample) increase the risk of an outlet going out of business.

In Winter & Szulanski (2001, p. 737) the authors asserted that "due to differences in the environmental conditions, modifications introduced to adapt the established template may create new problems; problems that will have to be solved in situ through a costly process of trial and error because they cannot be solved through reference to the established template. This is likely to slow down profitable growth." As shown in Winter et al. (2012) and Winter and Szulanski (2001), templates not only provide initial benefits, but these benefits remain over time. In the production teams we studied, we believe that a template serves as a good basis for individuals to hone their skills and for teams to learn how to cooperate with each other. Major process design choices are fixed through the template. Thus, learning can proceed faster within the team without the need to search and adapt the parameters of how the team works. Further, templates serve as a form of standardization that reduces performance variability between teams.

Ozkan-Seely, Gaimon and Kavadias (2015, p. 177) argued that although benefits from knowledge development are instantaneous, benefits from *knowledge transfer* are lagged "because of the difficulties in articulating and documenting knowledge as well as the challenges regarding its interpretation and application." In other words, although knowledge transfer may not bring initial performance advantages, the benefits of knowledge transfer only become apparent over time.

To illustrate this argument, consider that learning in our context has two components – *process* learning, as decision makers figure out how to best divide the labor among the different production team members, and *individual* learning, as team members figure out how to better execute their allocated tasks. Using a template 'locks' the process in earlier, enabling earlier repetition of tasks for individuals, thus enabling individuals to learn faster at their assigned tasks without having to alter their routines. Further, a proven template will lead to a more balanced division of labor within a team from the start, thus enabling all members of the team (and not just the bottleneck) to witness the impact of their performance on team outcomes, which in turn provides improved feedback for learning. Thus, using a template may speed up learning. Further, using the template will standardize performance across teams to some degree. With these arguments in mind, we present our next two hypotheses:

> HYPOTHESIS 1B*: Under low product/process change, template use leads to an increased learning rate after knowledge transfer, vs. local adaptation of the process.*

> HYPOTHESIS 1C: *Under low product/process change, template use leads to reduced performance variability between production teams vs. local adaptation of the process.*

It is intuitive that transferring knowledge through a template should lead to performance benefits if the template matches its destination context. However, production moves often imply change and the need to adapt. Will using a template in such changed contexts lead to less adaptation and thus decreased performance? Some academic argument favors deviating from an established template in a changing environment. Specifically, Victorino et al. (2013) analyzed the impact of service scripting on perceived service quality. A script is a "schematic knowledge structure held in the memory that specifies behavior or event sequences that are appropriate for specific situations" (Gioia and Poole, 1984), i.e., a type of template. They developed an experimental design that placed participants in either a standard service environment (e.g., hotel check in/checkout desk, low level of change) or a customized environment (e.g., hotel concierge desk, high level of change) in which participants were subject to a *predominant, moderate,* or *relaxed* script setting. The authors found that a relaxed script, when used in a customized environment, leads to higher performance. Blindly following a script in a customized setting might cause employees to "discount or ignore the greater variation in customer demands and customer signals" (Victorino et al. 2013, page 7).

Similarly, Winter et al. (2012), although empirically showing support for following a template when replicating a franchise environment, added a caveat to this result by saying that local adaptation should not always lead to business failure, especially when there are high population and cultural/institutional differences involved (Winter et. al. 2012).

Accordingly, some form of adaptation is needed if the recipient and source locations differ significantly. Such differences could be due to supplier, workforce, or environmental differences, or because the move is also used as an opportunity to alter the product. Using a template in this context may crowd out any effort by the recipient site to successfully adapt to change or will at least reduce the space in which recipients of the template are willing to search because they are anchored on the template. This leads to our second set of hypotheses:

> HYPOTHESIS 2A: *Under high product/process change, template use leads to lower initial performance (learning) after knowledge transfer, vs. local adaptation of the process.*
>
> HYPOTHESIS 2B: *Under high product/process change, template use leads to lower performance (slower learning rate) over time after knowledge transfer, vs. local adaptation of the process.*

2.3.2 Experimental Design

Operationalizing a Production Process and Template Use Condition

We used Lego building sets in our experiment to simulate a production process. There is a history of Lego building sets being used in academic laboratory research. In Reddy and Byrnes (1972), the researchers used “The Lego Man: A decision-making and problem-solving exercise” to show that when groups of middle managers were more compatible, they completed a Lego building task more rapidly than less compatible groups. In Ariely et al. (2008), the authors, via a Lego building exercise, showed that when subjects could see their finished work accumulate versus it being disassembled over time, they were far more productive. Norton et al. (2011) investigated the presence of the “IKEA effect” – the increase in valuation of self-made products. The authors sought to establish boundary conditions for this effect; so through building IKEA boxes, origami, and Legos, they found that people do put more value on products they build, but only if they were built successfully. Staats et al. (2012) used Lego building sets to study the effects of adding people to project teams. They found that although there are advantages to doing so, managers often underestimated the disadvantages, including coordination difficulties. Lastly, Moreau and Engeset (2016) assigned subjects a well-defined task – a Lego kit with step-by-step instructions — as well as an ill-defined task – a bag of Lego bricks and pieces. They demonstrated that those with a well-defined task did not perform well on subsequent ill-defined tasks that required creativity.

Nelson and Winter (1982) referred to a template as a working example of organizational routines that contained both critical and noncritical elements of the routine. These various elements “provide the details of how the work gets done, in what sequence and how various components and subroutines are interconnected” (Jensen and Szulanski 2007, pg. 1717). Although each Lego kit contained a set of step-by-step instructions on how to build the product, no guidance was given in these instructions for the most efficient way to build the device by dividing the labor among team members. To create a template, we ran a series of pretests to establish a template for making our initial product: The Lego Sunset Speeder (Lego No. 31017). In addition to the researchers, these pretests involved several teams of undergraduate students from the university’s Supply Chain and

Operations Club who spent a full day creating an optimal workflow design based on both speed and precision. In developing the template, we considered how many people were included in the team, roles, and responsibilities per team member, material flow, and the physical arrangement of each team member. Once the template was finished (see electronic appendix for all templates used), we used the same schema to generate the template for the product assembled in the *change* condition: The Lego Red Go-Kart (Lego No. 31030). Although the Red Go Kart and the Sunset Speeder are similar in some ways (e.g., four wheels, steering wheel, front and back bumpers, etc.), they also differ (e.g., dimensions/orientation of parts, colors, number of unique parts, etc.). The Sunset Speeder requires 32 steps for assembly, and the Red Go Kart requires 34 steps. Assembling either of these products involves assembling the chassis as well as building several subassemblies that can later be attached to the chassis. This represents change because the Red Go-Kart, despite being similar to the Sunset Speeder, differed in numerous ways from it. For the Red Go-Kart, we used the template format for the Sunset Speeder: the same number of workers with the same responsibilities. However, we adjusted the template to fit the specific references to the construction steps required for building the Red Go Kart.

Methods

We recruited 228 undergraduate and graduate students from the subject pool of a large Midwestern business school and divided them into 57 four-person teams. Each team was assigned to build a Lego device as quickly as possible with no defects for five rounds. In each round, teams started with a bag filled with unsorted Lego pieces. There were 15 teams in the "no template/change none" treatment; 14 teams in the "no template/change high" treatment; 14 teams in the "template high/change high" treatment, and 14 teams in the "template high/change none" treatment. As in past studies interested in learning effects (Epple et al. 1991; Darr et al. 1995, etc.), time acts as a proxy for cost in our experiment. Units judged defective had to be reassembled to conform to specifications before a round counted as complete; as such, quality defects only appear in our analysis as time delays.

Our unit of analysis in this study was the four-person production team. We varied two factors in the experiment: template use and change. We implemented these two factors in a full factorial between-subjects design. Therefore, teams were divided into four experimental conditions. Each team knew only of the experimental group it was in. In the *template* treatment, in addition to the instructions from Lego, the teams were given explicit directions regarding their production process, including details on material flow and division of labor. In the *no template* treatment, the teams got only the Lego instructions and were asked to organize themselves as they deemed best to accomplish the goal of building the device as quickly as possible with no defects. In the *no change* treatment, subjects assembled the Sunset Speeder, i.e., the device for which the template was designed. In the change treatment, the teams were asked to build the Red Go-Kart Lego device instead.

All teams were given five minutes to discuss their approach before the start of the first round. They were also given three minutes between rounds to reassess their approach and adjust their process. Note that we allowed the teams within all conditions to make changes between rounds. In that sense, in the template treatment, the template only represents a starting point for all teams. This design choice was made to allow adaptation by all teams across all experimental conditions. Study 2 will explicitly examine template use without such adaptation.

All participants were guaranteed $5 for completing the experiment, but teams had an incentive to deliver high performance because more money was possible based on a tiered compensation structure keyed to completion time. Each member of a four-person team received the same compensation as his or her teammates

2.3.3 Analysis and Results

During the planning phase before the first round, teams typically discussed unique strategies based on their experimental condition. When put into a template condition in which their positions and roles were initially fixed, they spent time discussing team responsibilities in detail as well as in creating a plan for how they could work together to best accomplish the goal. For example, each template team had three builders ("Builder 1," "Builder 2," and "Builder 3") and a fourth member in charge of instructions and material staging. The team member in charge of sorting materials would often ask, "how would you like for me to lay out the building materials?" Or "how would you like your instructions to be shared throughout each round?" Although the teams had structure, it was still important for members to coordinate effectively.

Conversely, in the no template treatment in which no structure was provided, the teams typically spent time discovering who had skills that were best suited to the task at hand. "Who is good at building things?" or "does anybody have experience with putting building sets together?" were common questions. Once roles and responsibilities were determined, it was not uncommon for the no template teams to eventually create a process like the template teams in which there were multiple builders and one person in charge of instructions and material flow. But the process of arriving at an efficient operation took time, and there was plenty of experimentation along the way.

Before diving into a more detailed statistical analysis, it is useful to examine our data descriptively. Table 2.1 lists descriptive statistics across different time periods and experimental conditions.

Table 2.1: Descriptive Statistics across Template Conditions[1]

Condition	Period	1	2	3	4	5
No Change No Template	Mean	14.75	10.39	8.39	6.46	6.32
	Std. Dev.	7.42	4.02	2.69	1.35	1.59
No Change Template	Mean	14.52	9.49	7.17	5.90	5.06
	Std. Dev.	3.03	2.98	1.33	1.10	0.91
Change No Template	Mean	15.92	9.67	7.27	5.90	5.24
	Std. Dev.	6.00	2.88	1.97	1.63	1.63
Change Template	Mean	14.46	8.99	6.17	5.57	4.84
	Std. Dev.	4.02	3.20	2.04	1.82	1.30

Notes. Time is measured in minutes required to complete a product according to specifications.

We make several observations. First, a learning curve pattern is clearly present in the mean durations across all conditions. Second, in the no change condition, both the

[1] One observation was removed before analysis. Specifically, one team in the template high condition refused to use the template in its first period, despite our explicit instructions to do so. The resulting time

means and standard deviations of observations are at all periods lower in the template condition than in the no template condition. This suggests that the template not only enabled teams to speed up on average, with time reductions between 9%-20% in rounds 2-5, but also that the template served to standardize performance across teams. Note that a similar pattern occurs in the change conditions, although the difference in means across template conditions is much less pronounced, and standard deviations across teams only differ in the first round.

To analyze our data more formally, we estimated a model that allowed us to differentiate learning curves across our experimental conditions. In accordance with H1A and H1B, we were especially interested in examining whether the parameters of the learning curve, i.e., the initial time to build the product (=*a*) and the learning rate (=*b*), changed across different experimental conditions. We applied the standard power law of learning in our model and used natural logs to linearize the model. Further, our model needed to account for the differences in learning curves across teams. Because we only observed teams for a few periods, we captured different learning curves across teams through random slopes and intercepts. Our model specification was as follows:

$$\begin{aligned}\ln\left(t_{p(i)}\right) = \ln\left(a_i\right) - b_i \ln\left(p\right) \\ +a_1 C_i + a_2 T_i + a_3 C_i \times T_i \\ +a_4 \ln\left(p\right) \times C_i + a_5 \ln\left(p\right) \times T_i + a_6 \ln\left(p\right) \times C_i \times T + \varepsilon_p\end{aligned}$$

In this specification, $t_{p(i)}$ refers to the duration of building the product for team *i* in period *p*. The constant a_i and the slope b_i are the parameters of the learning curve for team *i*, drawn from a multivariate normal distribution with standard deviations σ_a, σ_b and correlation coefficient ρ_{ab}. This aspect of our model allowed us to efficiently represent the data structure of multiple observations being nested in the same team while explicitly recognizing that the parameters of the learning curve of a team are likely correlated with each other so that longer initial task durations likely imply steeper learning curves. The dummy variables C_i and T_i (for change and template) capture the experimental condition of team *i* and shift both the intercept and slope of the learning curve. Finally, deviations from the power law of learning are permitted through the random error term ε_p, which is distributed normally with period specific standard deviation σ_p. This aspect of our model allowed us to capture heteroscedasticity in the data caused by later periods possibly exhibiting less noise than earlier periods. The model was estimated in Stata 14.2 using the "mixed" procedure. Results from the estimation are summarized in Table 2.2.

Table 2.2: Estimation Results from Random Effects Learning Curve Model[2]

Variable	Coefficient	Std. Error
Change	0.10	(0.11)
Template	0.05	(0.11)
Change×Template (H2A)	-0.13	(0.16)
ln(p)	-0.51**	(0.05)
ln(p)×Change (H2)	-0.17**	(0.07)
ln(p)×Template (H1)	-0.14*	(0.07)
ln(p)×Change×Template (H2B)	0.13	(0.10)
Constant	2.61**	(0.08)
σ_a	0.25**	(0.04)
σ_b	0.11**	(0.04)
ρ_{ab}	-0.71**	(0.14)
σ_1	0.21**	(0.04)
σ_2	0.21**	(0.02)
σ_3	0.17**	(0.02)
σ_4	0.15**	(0.02)
σ_5	0.16**	(0.02)
N	284 [57]	
χ^2	689.75**	

Notes. **p≤0.01; *p≤0.05; N refers to the number of observations, with the number of teams in brackets.

Several findings emerged from our analysis. None of the direct treatment effects or their interaction terms were statistically significant. This indicates that the initial time to build the product was similar across all experimental conditions. This finding rejects both Hypotheses 1A and 2A, which predict differences in initial performance. However, the learning factor interacts with the treatments in our experiment, indicating that learning changed under different treatments. We also note that both variances in random

[2] Note that one observation from one team in the first round was removed from the analysis – this team, despite being in the template "high"' condition ignored our requirement to follow the template strictly in the first round. Consequently, its performance was 16 minutes slower that the next slowest team in that condition.

slopes and intercepts are significant, indicating that teams vary widely in the origin and shape of the learning curve; unsurprisingly, the correlation coefficient between these random slopes and intercepts is negative and significant, indicating that teams that initially took longer also had faster progress ratios. Hypothesis 1B argues that template use will lead to higher learning rates, which is supported ($b=-0.14$, $p \leq 0.05$). This is in line with our arguments related to the delayed impact of knowledge transfer through templates (see Ozkan-Seely et al. 2015). Using a template indeed speeds up learning, quite possibly by allowing individual team members to become experienced in their tasks faster.

Hypothesis 2B argues that this performance improvement should not be visible and may even turn negative if product/process change is high. This hypothesis received only mixed support: Template use leads to essentially no difference in the learning factors if change is high ($b=0.13-0.14=-0.01$); as predicted, they did not seem to benefit from the template. However, the template did not hinder their learning as the experiment progressed either. Further, teams in the change condition generally had faster learning factors than no-change teams ($b=-0.17$, $p \leq 0.01$).

H1C argues that template use within a low-change environment will lead to a reduction in performance variability between teams. To test this idea, we re-estimated our model in the no change condition, allowing the error variance to vary by template. See Table 2.3 for the results. The model estimates show that the residual variance in the template condition ($\sigma=0.14$ (s.e.=0.02)) was much lower than the residual variance in the no template condition ($\sigma=0.20$ (s.e.=0.02)). Compared to a model with equivalent residual variances across conditions, this model with different residual variances leads to an improvement in χ^2 by 214.91-194.04=20.83, which is a significant improvement in model fit ($p \leq 0.01$). Therefore, H1C is supported. A similar analysis[3] for the change condition revealed a small improvement in χ^2 by 703.24-702.85=0.51, a difference that is not statistically significant. Performance across teams was thus better standardized with the template.

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[3] Note that the random effects variance for the slope in the change condition was close to zero, and thus these random effects were removed from the estimation.

2.4. Study II - The Copy Exactly Approach

As mentioned in the Introduction, Intel is known for its Copy Exactly method for knowledge transfer. Intel developed this method to minimize the time spent in a transfer to maintain product quality and production yields in line with expectations (McDonald, 1998). Instead of the traditional approach in which matching the final product is the sole focus, Copy Exactly focuses on four levels of matching between source and recipient sites: physical inputs, process/equipment parameters, module outcomes, and final product specification. For Intel, this approach has yielded the desired results because new factories are brought online faster and deliver yields consistent with the source location. Also, if improvement ideas are generated during the installation of new lines, the ideas are tested and implemented across all lines (source location and recipient locations) so that improvements are made consistently in the network (McDonald, 1998). Terwiesch and Xu (2004) extended Intel's Copy Exactly idea to describe a ramp-up strategy in which, after introduction of a process into a production facility, a firm prohibits any changes in the process until enough time has elapsed that the process can produce large market-ready quantities.

Table 2.3: Results Using Different Residual Variances across Template Conditions

	No Change		Change	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Template	0.05	(0.12)	-0.07	(0.10)
ln(p)	-0.51^{**}	(0.06)	-0.69^{**}	(0.04)
ln(p)×Template (H1)	$-0.14^{\dagger}$	(0.08)	-0.02	(0.05)
Constant	2.61^{**}	(0.09)	2.71^{**}	(0.07)
σ_a	0.17^{**}	(0.04)	0.22^{**}	(0.03)
σ_b	0.28^{**}	(0.05)	-	-
ρ_{ab}	-0.85^{**}	(0.08)	-	-
$\sigma_{Template}$	0.14^{**}	(0.02)	0.18^{**}	(0.02)
$\sigma_{No\ Template}$	0.20^{**}	(0.02)	0.17^{**}	(0.02)
N	145 (29)		139(28)	
χ^2	214.91^{**}		703.24^{**}	

Notes. $^{**}p\leq0.01$; $^{*}p\leq0.05$; $^{\dagger}p\leq0.10$. N refers to the number of observations, with the number of teams in brackets.

In Study I, templates were only initially enforced, and teams could subsequently modify the template. This conceptualization of template use does not correspond to Copy Exactly because process parameters and module outcomes can change after the first round of the experiment. Using Copy Exactly instead, i.e., not allowing any process modifications as time progresses, corresponds to higher standardization. At the same time, it reduces adaptation and the sense of ownership with recipients. Thus, Study II examined whether the benefits of standardization inherent in Copy Exactly outweigh the potentially negative behavioral responses from recipients.

2.4.1 Theory

To explain what we may expect when using the Copy Exactly strategy, we draw upon the findings from organizational behavior on individual and team level motivation. Bernstein (2012) tested the implications of a transparent (accurate observability) organizational design on workers' productivity and organizational performance in the setting of a large Chinese contract manufacturer of mobile phones. Transparency in this study can be thought of as a form of standardization (e.g., template use) in which the goal of the firm is to maintain operational control and the desired levels of productivity. The author concedes that transparency may improve a unit's access to the expertise, experience, and stored knowledge of another unit — thereby increasing the quantity and quality of knowledge transfer. But it may also "counter-intuitively reduce their performance by inducing those being observed to conceal their activities through codes and other costly means" (Bernstein 2012, p. 181) to avoid trouble with management. Through experimentation within the contract manufacturer, they found that by creating "zones of privacy" for groups of workers, the firm significantly increased line performance by supporting productive deviance, localized experimentation, and continuous improvement. Within these zones of privacy, workers could use their own methods to build and pack mobile phones, versus the standardized managers' methods. The workers also took the opportunity to switch roles among themselves so they could train for the future. In the same way, although template use has its merits — especially as it relates to operational control — we believe there is a point at which too much operational control adversely affects individual and team performance. Bernstein (2012) demonstrated that there is a certain level of empowerment that should be extended to employees. Otherwise, their full capabilities will not be tapped, which could lead to reduced performance.

Zhang and Bartol (2010), interested in understanding if/how psychological empowerment is linked to employee creativity, developed a theoretical model and then empirically demonstrated that psychological empowerment is positively linked to intrinsic motivation and employee creativity. Mathieu et al. (2006) sought to test a proposed link between team empowerment and both customer satisfaction and quantitative performance by gathering empirical data from customer service engineers at a major office equipment and technology organization. Through survey responses, they found that team empowerment led to improved team processes and ultimately to improved customer satisfaction and quantitative performance. They argued that “to the extent team members are empowered, they will be liberated to better execute transition and action processes as they see fit…coordinate their own actions and otherwise align their collective efforts with work demands to meet their performance goals” (p. 101). These examples show that although some structure is needed to ensure workers are aligned with company goals, too much structure without worker input can have adverse behavioral consequences.

We can also look at the literature on organizational creativity to find theory in favor of deviating from the status quo. Shalley and Gilson (2016) address the idea of balancing creativity and standardization and argue that creativity is essential for societal and economic growth. Further, they state that with the creativity process “it is important to first engage in processes that challenge the status quo, move away from established ways of doing things and seek out new approaches to how work is performed”. This process involves “searching broadly for diverse information, seeking out new approaches, linking ideas from multiple sources, generating solutions and elaborating on the ideas developed” (pg. 5).

Within our experiment, making the template rigid reduced autonomy for workers, thereby making the task a simple execution of a process design that the workers have no ownership in. Without ownership, the task is very transactional, reducing the workers’ sense of empowerment, motivation and creativity. Without empowerment, intrinsic motivation and the ability to create, the workers may attribute poor performance more to the system (i.e., the process handed to them) than to themselves, reducing their effort as well as their motivation to improve further. With that in mind, we propose the following hypotheses:

> HYPOTHESIS 3A: *The Copy Exactly approach will lead to lower initial performance (learning) versus Template Use with the ability to search and adapt.*
>
> HYPOTHESIS 3B: *The Copy Exactly approach will lead to a slower learning rate over time versus Template Use with the ability to search and adapt.*

2.4.2 Experimental Design

The 30 teams in Study II used the same template for the Sunset Speeder and Red Go Kart devices as the teams in Study I. Unlike Study I, none of the Study II teams could deviate from the template between rounds. The only adaptation they could make was that team members could switch roles. Other than the strict adherence to the template, Study II was conducted in the same way as Study I. Our theory from the previous section applies to both the Change and the No Change conditions, since the only necessity for the effects underlying H3 is the existence of the template, independent of the product for which the template was designed. For completeness, we ran our experiment in Study II under both Change and No Change conditions, expecting a similar effect of Copy Exactly under both conditions.

Data from Study II was merged for analysis with the template condition data from Study I. We recruited 120 undergraduate and graduate students from the subject pool of a large Midwestern business school and divided them into 30 four-person teams. Each team was assigned to build a Lego device as quickly as possible with no defects, for five rounds. There were 15 teams in the copy exactly/no change experimental condition and 15 teams in the copy exactly/change condition.

2.4.3 Analysis and Results

Table 2.4 lists descriptive statistics of our data across different time periods and experimental conditions. We merged the template data from Study I with the copy exactly data in Study II so that we could examine differences between the two approaches (template use with search, Study I vs. template use without search, Study II). The no-copy exactly teams outperformed the copy exactly teams in every round by a significant margin.

Table 2.4: Descriptive Statistics across Template Conditions[4]

	Period	1	2	3	4	5
No Change No Copy Exactly	Mean	14.52	9.49	7.17	5.90	5.06
	Std. Dev.	3.03	2.98	1.33	1.10	0.91
No Change Copy Exactly	Mean	18.74	11.79	9.19	7.13	7.23
	Std. Dev.	4.74	4.20	4.39	1.42	2.97
Change No Copy Exactly	Mean	14.46	8.74	5.97	5.44	4.63
	Std. Dev.	4.02	3.18	1.97	1.83	1.08
Change Copy Exactly	Mean	18.33	9.55	7.26	6.54	5.24
	Std. Dev.	3.41	2.60	2.40	2.22	1.01

To proceed with our analysis, we estimated an empirical model like the one estimated in Study I. We used change and copy exactly, as well as their interaction, as independent variables in the analysis. The model was estimated in Stata 14.2 using the "mixed" procedure. Results from the estimation are summarized in Table 2.5 below. Several findings emerged from our analysis. First, the direct treatment effect of Copy Exactly is statistically significant and positive, which means that the initial time to build the product was longer under Copy Exactly than under the non-copy exactly treatment in the No Change condition. This finding supports Hypothesis 3A, which predicts an initial performance deficit when employing the copy exactly approach. Second, the learning factor does not interact with the treatments in our experiment, which indicates that the learning rates between Copy Exactly and Non-Copy Exactly are the same.[5] This finding rejects Hypothesis 3B, which predicted a slower learning rate for the Copy Exactly approach. However, because the Copy Exactly approach drives a much slower startup versus the non-copy exactly, the fact that their learning rates are the same is somewhat

[4] Note that as in Study I, the performance in the first round from one team has been removed from the analysis.

[5] Note that the ln(p)×CopyExact interaction in Table 6 measures an effect that is different from the ln(p)×Template interaction in Table 2. Under No Change, the latter effect measures the difference in learning rates between Template and No Template conditions, while the former measures the difference between Templates under Copy Exact and Non-Copy Exact.

moot because a significant performance gap remains between both approaches throughout the experiment. This gap delivers a roughly 19% slower processing time across the entire experiment. To put that in perspective, over a standard eight-hour shift, non-Copy Exactly teams can build the same number of products in 6.5 hours that it takes the Copy Exactly teams 8 hours to produce.

As expected, Copy Exactly seems to influence template use similarly under Change and No-Change conditions, since the direct effect, as well as all interactions with Change are non-significant. In other words, Copy Exactly leads to an adverse motivational response that manifests itself in increased processing times within teams compared to Non-Copy Exactly, independent of whether the Template was developed for the product in question, or for a related similar product.

Table 2.5: Estimation Results from Model of Random Effects Learning Curve

Variable	**Coefficient**	**Std. Error**
Change	-0.04	(0.09)
CopyExact	0.21**	(0.09)
Change×CopyExact	0.02	(0.12)
ln(p)	-0.65**	(0.04)
ln(p)×Change	-0.05	(0.05)
ln(p)×CopyExact	0.01	(0.05)
ln(p)×Change×CopyExact	-0.07	(0.07)
Constant	2.66**	(0.07)
σ_a	0.18**	(0.03)
σ_b	0.05	(0.07)
ρ_{ab}	0.05	(0.94)
σ_1	0.17**	(0.04)
σ_2	0.21**	(0.02)
σ_3	0.21**	(0.02)
σ_4	0.14**	(0.02)
σ_5	0.15**	(0.02)
N	285 [57]	
χ^2	1457.82**	

Notes. $^{**}p \leq 0.01$; $^{*}p \leq 0.05$; N refers to the number of observations, with the number of teams in brackets. Numbers are expressed in natural log form.

2.5. Discussion

The questions guiding our research in this chapter are "does template use lead to higher performance than local adaptation when transferring production process knowledge?" and "does rigidly enforcing a template result in adverse behavioral consequences at the recipient site?" Although a move is complex and involves a variety of decisions, at the heart of the move is an exercise in *knowledge transfer* and the choice of whether to use a template exclusively (e.g., Intel's Copy Exactly) or to adapt the template locally to fit the characteristics of the recipient site. Until now, this debate was waged primarily in the strategy literature (Winter and Szulanski 2001, Jensen and Szulanski 2007, Szulanski and

Jensen 2008, Winter et al. 2012) with the studies focused on firm or store unit performance in a low change, service context. In our research, we tested the merits of template use under low and high change at the team level within a manufacturing context. We also sought to empirically test the merits of Intel's Copy Exactly technology transfer strategy, which had not been done outside of Intel. Study I shows that when moving production processes between similar settings, using a template to transfer process knowledge may not lead to an initial difference in performance, but does lead to better performance (faster learning) over time than attempting to create a new process in the recipient location. The lack of an initial difference in performance is consistent with Ozkan-Seely et al. (2015, pg. 177) who argue that while benefits from knowledge development are instantaneous, benefits from *knowledge transfer* are lagged "because of the difficulties in articulating and documenting knowledge as well as the challenges regarding its interpretation and application."

In Study II, we find that there are limits to the benefits of template use. If the template is rigidly enforced, without the ability for the recipient teams to search for ways to adapt it, performance can suffer. Teams in the Copy Exactly conditions have similar learning rates, albeit higher learning curve intercepts, than teams in the Non-Copy Exactly conditions. This leads to a performance gap of approximately 19% in processing times across all five periods in the experiment.

While overall processing times under Copy-Exactly were slower than under Non-Copy-Exactly, it was surprising to us that learning rates for Copy Exactly and Non-Copy Exactly teams were similar. A possible explanation for this observation could be that the template reduces the need for process learning - division of tasks, product flow, etc. - within the recipient teams by transferring an optimized layout and workflow from the source team. Learning in the template teams is thus mostly individual learning – team members becoming more experienced at their allocated tasks. Such learning may happen more subconsciously, and be less dependent on effort and motivation than process learning. As a result, learning for both conditions where templates are employed happens similarly.

If we take the results from Study I and II together, when moving production between manufacturing environments, managers should ensure that a template is utilized and that the intended recipients of the template have the flexibility to adapt it and participate in the design of their work. Of course, in certain industries, regulations may limit the ability to deviate from a template. Also, *process complexity* could be a factor that influences whether a firm should strictly rely on a template. A process may be so complex that the successful execution of it at the recipient site is causally ambiguous (Szulanski 1996). In that case, the firm may choose to avoid risk by keeping the process the same as it was in the source location. We hope that future research examines process complexity here as a possible moderator.

Although our study makes an important contribution to the field's understanding of process moves, template use, and knowledge transfer, it has limitations. The laboratory approach we use emphasizes internal over external validity (Siemsen 2011). Thus, further testing our insights in the field would be valuable. Further, creating a way to reliably measure quality as a dependent variable would be a worthwhile contribution. In addition, we manipulated change only through a product change; additional forms of change, such as materials or labor, would be useful to study as well.

Our research provides further evidence that using templates is an important aspect of process moves; the benefit of a template is not that initial performance increases, but rather that learning happens at a much faster rate, reducing the time to bring the process to productive levels. The template serves as a key input (Gladstein, 1984; Guzzo and Dickson, 1996, Mathieu et al. 2000) to creating a shared mental model for the team to use while working together (Mathieu 2000). These models help facilitate both *team* related and *task* related benefits which are vital to team success.

Building on the results of chapter 2 and based on discussions with a multinational plastics molder, chapter 3 investigates a factor that may impede or enhance a firm's ability to transfer process knowledge during a production move: *Functional Diversity*.

Chapter 3:

Functional Diversity and its Impact on Knowledge Transfer Effectiveness

3.1. Introduction

Firms are often pressured by their customers or competitors to adapt and move their production processes within and between countries. Such a shift in process location is often not a trivial exercise, requiring the impacted parties to head down a new learning curve. A firm's goal is to minimize this disruption by carefully managing the knowledge associated with the production process.

While knowledge creation (Nonaka, 1994) and knowledge retention (Argote et al. 1990) are both key in ensuring production move success, *knowledge transfer* (Argote, 2013) is at the heart of a production process move. The risk of failing to transfer knowledge during a move is arguably high. Therefore firms spend considerable time and effort to prepare for and ensure the successful knowledge transfer during a move. Typical practices include creating standard operating procedures (SOPs), service scripts, and even special methodologies like the "Copy Exactly" approach from Intel (McDonald 1998) to ensure that knowledge transfer is effective. In this study, we investigate the role of ***functional diversity*** in enhancing/eroding knowledge transfer effectiveness when using templates.

Executing work in teams is a key element of today's successful, innovative firms (Ichniowski, Shaw 1999). Be it a new product launch, a cost-savings initiative or a production process move, organizations tend to pool the collective expertise, perspective and effort of various people throughout the organization to accomplish tasks. With this reliance on teams, there has been much debate within the academic literature on how to structure them (Ancona and Caldwell, 1992). When considering a production move, much of the work that determines the success or failure of the move involves knowledge transfer between a source and a recipient team. Knowledge transfer means learning indirectly from the experience of others, and often occurs across a boundary, e.g. organizational units, groups or geographies (Argote and Miron-Spektor, 2011). Such boundaries can imply barriers to knowledge transfer, which in turn reduce the effectiveness with which a transfer can happen. As seen in Kent and Siemsen (2017), even when a proven template is used in the transfer, the benefit of the knowledge to the recipient is lagged. If there are additional factors that extend this lag, a firm is at a heightened risk of missed shipments, lost revenue and potential damage to supply chain relationships.

Knowledge transfer in a production process move is occurring across plant boundaries. We know from past studies that characteristics of the source and recipient boundary units, such as their *absorptive capacity* (Cohen and Levinthal, 1990), *similarity* (Darr and Kurtzberg, 2000) and *relationship quality* (Szulanski 1996, Zollo and Reur 2010) matter. A factor that has not been analyzed in this context is the between team *functional diversity*, which is the extent to which *education, experience and expertise* (Jehn et al., 1999) of team members across different teams differ. Typically, research studies "within team" functional diversity, but when it comes to process moves, where there is a *source* location sending a production process to a *recipient* location, there is also "between team" functional diversity to consider. We therefore ask the following research question: <u>Does functional diversity impact the effectiveness of a proven template when transferring production process knowledge</u>?

To investigate this question, we take a behavioral approach. Even though production process moves are complex and multidimensional, at the core of a move is an exercise in effective knowledge transfer and task understanding; both of these topics lend themselves to behavioral research. In our behavioral experiments, teams repeatedly build a device using a proven template that was encoded by other participants from similar or dissimilar functional backgrounds to assess if between-team functional diversity impacts performance. Before we discuss our behavioral experiments, we illustrate the role of functional diversity during a process move by looking at the example of Far East Molding (FEM)[6] and a move the company made in the early 2000s.

FEM is a precision plastic molding company with manufacturing operations in China and Thailand. The company was founded several decades ago, and has grown by working in the consumer electronics, household goods, hard disk drives, automotive and healthcare industries. Due to the nature of their products, they are typically a second tier supplier. However, since FEM is highly skilled, they are usually given responsibility for key subcomponents, like the plastic housing and filtration systems for hard disk drives. The company's yearly revenue is approximately $50-$100 million.

In the early 2000s, their hard disk drive (HDD) customers asked FEM to move the component making process from China to Thailand to be closer to finished goods production. FEM agreed and began to establish a team in the source location (China) as well as a recipient team in Thailand. Since FEM had never operated in Thailand, team composition became an early and important topic to address. FEM organized production process specialists at their China facility to serve as the "source" team transferring process knowledge to the Thai facility. This group was primarily made of Engineering and Production specialists who had been working on the production process for several years. Since the recipient facility was brand new, FEM thought it best to establish a recipient team comprised of various functions that could play a role on the project from a business and technical point of view, including: Legal, Finance, HR, Government Relations, Sourcing, Engineering. For over a month, the transfer dyad (source and recipient teams) had difficulty executing the project schedule, driven in large part by the divergent interests that each team represented. The source team grew frustrated by the lack of focus among the recipient team, as meetings often ranged a variety of non-technical topics such as supply chain development in Thailand, material sourcing, budget concerns, etc. While these topics were important, they did not pertain directly to the expertise and background of the source team members. This lack of focus was due in large part to not having recipient team members who could effectively communicate with the source members on the technical matters of the project. Ultimately, FEM's

[6] We use the name "Far East Molding (FEM)" to conceal the actual identity of this company.

management decided to take two actions: one was to fully invest in technical personnel at the recipient site who could communicate with the source team and receive their knowledge of the HDD component making process. Second, FEM divided the transfer dyad into two: one dyad focused on the technical needs of the process move and the other dyad focused on the business needs of the move. These changes proved effective and allowed FEM to meet their 12 month transition timeline, as the technical source team was finally able to focus on the technical needs of the move, sharing key details of the process and training the recipient team along the way. FEM discovered that having functional diversity between teams was inefficient, demotivating and unproductive.

The remainder of the paper is presented in the following manner: In section 2 we examine relevant literature, identifying research gaps that we plan to address. Section 3 develops the hypotheses that are grounded in theory developed from relevant literature. Section 4 presents the empirical setting and data, and in section 5 we discuss our analytical results. Lastly, in section 6 we highlight the strategic and operational implications of this study, its limitations and explore future research directions.

3.2. Relevant Literature

Functional Diversity

The topic of functional diversity has been discussed among management/strategy scholars for over 20 years. There are several noteworthy studies for our particular context. A more complete literature review is given by Bunderson and Sutcliffe (2002).

In a seminal study, Ancona and Caldwell (1992) collected data from 409 people across 45 new product development teams within five high technology companies. A key finding in their research is that functional diversity drove increased communication within and outside the team, leading to a higher team innovation rating when judged by management. Despite this higher innovation rating, the overall effect of functional diversity on team performance was negative. The authors argue that while diversity may bring more creativity to the product development process, it impedes implementation of a newly developed product. This impediment may be caused by the fact that the various functions with a team are like different "'thought worlds' each focusing on different aspects of technology-market knowledge, and making different sense of the total" (Dougherty, 1992).

Jehn et al. (1999) studies three types of team diversity: social category, value and informational diversity. *Informational* diversity can be thought of as differences in knowledge bases that various members bring to the group. These differences have their roots in the variety of education, experience and expertise between team members, i.e. a concept that is close to functional diversity. The authors hypothesize that while informational diversity increases both **task** (what to do) and **process** (how to do) conflict, it also would increase performance (work team productivity). Using data collected via survey of 485 employees within a top household goods moving company, they found that informational diversity led to increased levels of conflict and it also led to increased performance, especially when tasks were complex. "Research has demonstrated that differences in educational background lead to an increase in task-related debates in work teams" (Jehn et al., 1997).

Instead of functional diversity, Van Der Vegt and Bunderson (2005) examined "expertise diversity" and its impact on multidisciplinary team learning and performance. They recruited 57 teams within one oil and gas company. As part of their study's motivation, the authors share two conflicting views on the role of expertise diversity by the 19th century philosopher John Stuart Mill, showing why this is not a simple and linear subject to study. Mill states that "It is hardly possible to overrate the value…of placing human beings in contact with persons dissimilar to themselves...such communication has always been, and is particularly in the present age, one of the primary sources of progress" (Mill, 1848). However, Mill also states 20 years later that "intimate society between people radically dissimilar to one another is an idle dream. Unlikeness may attract, but it is likeness which retains" (Mill, 1869).

Via surveys, the authors analyze how performance (supervisor ratings) of these teams would be impacted by *collective team identification,* which is the extent to which members feel emotionally attached to their team, and *team learning behaviors,* which are "activities by which team members seek to acquire, share, refine or combine task-relevant knowledge through interaction with one another" (Van Der Vegt and Bunderson 2005).

They found that expertise diversity did not affect performance in a linear fashion. Its impact on performance was moderated by collective team identification and partially mediated by team learning behaviors. They also find that independent of collective team identification, expertise diversity was most strongly associated with performance at moderate levels of diversity. These findings appear to be consistent with Sampson (2007, see below) who also found that moderate levels of diversity are most suitable. While this study is informative, the subjective manner in which it measures performance (supervisor ratings) could leave the results open to speculation. In our study, we choose to take an objective approach to performance (completion time i.e. cost) and have clearly defined roles for each team member within our experiment to alleviate concerns regarding team performance.

Sampson (2007) is one of the few papers in this stream of research that does not focus on "within team" diversity but instead looks at "between team" diversity. Specifically, the author analyzes the impact of partner technological diversity on firm innovative performance after an alliance. The concept of technological diversity is similar to functional diversity except that in the Sampson study, technological background of the firm is considered instead of individual or team functional specialization. The paper discusses how "R&D collaborations present unique coordination challenges, since some sharing or transfer of knowledge over firm boundaries is usually required. Successful knowledge transfer is not assured, particularly when knowledge is tacit or complex" (pg. 364). Knowledge transfer in this context is made even more complicated when considering a firm's desire to avoid unintended spillover effects when exchanging information with their alliance partner. The author provides arguments that technological diversity should be either low or high, and then hypothesizes that a ***moderate*** level of technological diversity will lead to increased firm innovation, measured by post alliance patents. Using data from 463 R&D alliances involving 487 firms in the telecommunications equipment industry, the study finds that increasing technological diversity improves firm innovative performance. However, beyond a certain point, the innovative performance declines as technological diversity increases further. Therefore, their hypothesis is supported.

This study offers a nuanced perspective for how diversity between two teams can impact innovation performance. However, there are a couple of key differences between Sampson (2007) and our study. First, while Sampson (2007) studied two separate firms forming an alliance, we are looking at two teams within the same firm. There is no concern of spillover effects stemming from sharing too much information in our context. Also, while Sampson (2007) solely focused on innovation, our study examines execution at the recipient site as well. This is an important distinction because within this literature stream, there is substantial consensus that functional diversity leads to improved idea generation. But what is at debate is how does this same diversity work together to turn those ideas into reality that can lead to top and bottom line results. Our study seeks to address this question by gathering data generated by teams executing the ideas of teams with similar and dissimilar functional backgrounds.

Boone and Hendricks (2009) focus on the functional background of top management teams (TMTs) and how the variety of knowledge and cognitions created by functional diversity impacts decision quality and ultimately firm performance. They argue that functional diversity can only be unleashed at the TMT level when there is strong collaboration among team members, accurate information exchange and decentralized decision making. With data from 33 European information technology firms, they find that functional background is positively related to firm performance when there is accurate information exchange, truly collaborative behavior between team members, and decentralized decision making. This study is informative because as we think of how using a proven template may be impacted by functional diversity, Boone and Hendricks (2009) would argue that if the information in the proven template is communicated accurately by the source team function, and the recipient team members work well together and share decision making responsibility, the between team functional diversity should lead to increased learning and overall performance.

In summary, the potential benefits of functional diversity have been discussed for over 20 years within the management/strategy literature. But very little research has examined how functional diversity impacts knowledge transfer, or how it impacts manufacturing performance. Also, past studies primarily investigate ***within*** team functional diversity, while our study focuses on ***between*** team functional diversity.

3.3. Theory

As mentioned previously, Ancona and Caldwell (1992) empirically tested the merits of functional diversity and found that while the presence of functional diversity improve communication within and outside of the projects teams, functional diversity does not have a positive relationship with team performance or innovation. They argue that having functional diversity "impedes implementation because there is less capability for teamwork than there is for homogenous teams."

In Dougherty (1992), the author is interested in uncovering potential barriers to successful product innovation. The authors talks about how "the styles in which people organize their thinking and action about innovation-their 'interpretive schemes'-are major barriers to linking and collaboration" (p. 179). One such barrier is that each department (or function) is like a different "thought world", each focusing on different aspects of available knowledge, and making a different sense of the knowledge. Further, the organizational routines within each department exacerbate, rather than coordinate, these thought worlds, which constricts potential learning. The author contends that two aspects of each thought world are relevant to product innovation: its "fund of knowledge" or what they know, and its "systems of meaning" or how they know. "Thought worlds with different funds of knowledge cannot easily share ideas, and may view one another's central issues as esoteric, or meaningless. A thought world also evolves an internally shared system of meaning which provides a 'readiness for directed perception' based on common procedures, judgments and methods, The systems of meaning produce an 'intrinsic harmony' for the thought world, so ideas that do not fit may be reconfigured or rejected outright." (Dougherty, 1992, pg. 182).

During a production process move, usually current business is being transferred from one location to another, and it is vital that it is done so without delay. Since a move involves a recipient team receiving both explicit and tacit knowledge from a source location, if they are derived from different thought worlds, they may selectively pick and choose information that lines up with their previous understanding, ignoring information that may be equally important to delivering the necessary performance. The inclusion of different thought worlds between the source and recipient teams may also limit the opportunity for collective learning, as each group may think they know all there is to know. This lack of coordination during a move could lead to a reduction in initial learning, which is the speed in which the recipient team ramps up to the expected level of performance.

Consistent with rationale in Jehn et al. (1999), we would also expect conflict to increase when knowledge is transferred between functionally diverse teams because bringing together teams with different educational backgrounds could lead to an increase in task-related debates (Jehn, 1999; Stasser, 1992). With these perspectives in mind, we present the following hypotheses:

> *HYPOTHESIS 1. Between team functional diversity leads to reduced performance when transferring production process knowledge.*
>
> *HYPOTHESIS 2. Between team functional diversity leads to increased levels of task and process conflict when transferring production process knowledge.*

3.4. Empirical Setting & Methods

Operationalizing a Production Process and Functional Diversity

In our experiment, we used Lego building sets to simulate a production process. There is an extensive history of Lego building sets being used in rigorous academic research, not to mention being used within corporate and university settings to examine real world phenomena. In Ariely et al. (2008), the authors analyzed the role of productivity by having male undergraduate subjects build a 40-piece Bionicle Lego model over and over with a declining wage for each subsequent model built. Subjects were in either the "meaningful" condition, in which they would be able to see the models they finished over the course of the entire experiment. Otherwise, they were in the "Sisyphus" condition in which each finished Lego model was disassembled after completion. The researchers found that the subjects in the meaningful category built significantly more Lego Bionicles than those in the Sisyphus condition. Staats et al. (2012) use Lego building sets to study the effects of adding people to project teams and find that while there are advantages of doing so, managers often underestimate the disadvantages, including coordination difficulties. They term this the "team scaling fallacy" and introduce reasons why this occurs. Moreau and Engeset (2016) assigned subjects a well-defined task – A Lego kit with step-by-step instructions – as well as a ill defined task – a bag of Lego bricks and pieces. They demonstrated that those who began with a well-defined task did not perform well on subsequent ill-defined tasks that required creativity. Lastly, in Kent and Siemsen (2017), the authors examine the role of template use when transferring production process knowledge. A template is defined as a working example of organizational routines that contain both critical and noncritical elements of the routine (Nelson and Winter, 1982). Using Lego building sets and 87 teams of 4 people, the authors demonstrate that using a template leads to better performance than not using one. A template also leads to reduced performance variability between teams.

Functional diversity is operationalized as follows: First we recruited multiple 4-person teams of either Engineering or Business students to serve as our source teams. Each of these source teams was asked to encode the template given to them. By encode, we mean that the teams were verbally instructed to use a particular process to build the device, they then made the device multiple times using this process, and were then asked to codify what they experienced into a written template so it could be used by future *recipient* teams. This process ensured that all source teams were encoding the same process, such that differences between templates across source teams were due to the encoding process, and not due to fundamentally different processes being encoded. Then, a written template was chosen[7] that best represents the process it was derived from. Once the two templates (one for Engineering, one for Business) were chosen, 120 students with a Business background and 120 students with an Engineering background were recruited from a large Midwestern university and randomly divided into teams of 4 people within each function, all serving as the "recipient" teams for the process knowledge being transferred.

[7] Supply Chain Ph.D. students were recruited to choose which template would represent the Engineering and Business "source" teams. They made their choice based on clarity of the template as well as accuracy vs. the original process.

Methods

We divided the 240 subjects into 60 teams of 4. Each team was asked to build a Lego device (Sunset Speeder – 31017) as quickly as possible with no defects, for five rounds. As in past studies interested in learning effects (Epple et al. 1991; Darr et al. 1995, etc.), ***time*** acts as a proxy for cost in our experiment. Units judged to be defective had to be reassembled to conform to specifications before a round counted as complete; as such, quality defects only appear as time delays in our analysis.

Our unit of analysis is the four-person production team. We varied two factors in the experiment: Template Origin and Template Destination. We implemented both factors in a full factorial between-subjects design, so we divided the teams into four experimental conditions (2 x 2). Each team only knew of the experiment group it was in. When the template origin and destination were the same function (e.g. Business to Business), functional diversity could be considered "low". Conversely, when the template origin and destination were different (e.g. Engineering to Business), functional diversity could be considered "high". To make the origin of the template salient to the recipient teams, they were informed where the template came from before starting the experiment.

All teams were given five minutes to discuss their approach before the start of the first round. They were also given three minutes between rounds to reassess their approach and make adjustments to their process, if necessary. Note that we allowed the teams within all conditions to make changes between rounds. We had each team self-report their changes and we tracked them to determine the level of task and process conflict within the experiment (see section 3.4.2 for more details). All participants were guaranteed $5 for completing the experiment, but teams had an incentive to speed up their production since their total compensation was linked to their team's completion time (the Appendix contains a complete set of instructions for experiments).

Jehn et al. 1999 states that when teams disagree on "what to do" within a task assignment, that is *task* conflict. When they disagree on "how to do it" within a task assignment, that is *process* conflict. We use self-reported changes[8] as a proxy for conflict

[8] Self-reported changes are the unique ideas generated between each round. These ideas were self reported by each participating team and independently validated by two PhD. candidates.

because it shows teams not content with doing what has been given to them, so they are searching for an optimized solution. Since we are interested in understanding if functional diversity causes *task and process conflict*, we use the number of changes made to the process each round as a proxy for task and process conflict. We view the number of changes as a good proxy for conflict because this measure shows the team's dissatisfaction with the template they have been given. These process changes were self-reported by each team when they were given time between rounds to discuss their process and how it could be improved.

3.4.2 Analysis and Results

Before diving into a more detailed statistical analysis, it is useful to examine our data descriptively. Table 3.1 lists descriptive statistics across different time periods and experimental conditions. We make several observations. First, a learning curve pattern is clearly visible in the mean durations across both Functionally Diverse and non Functionally Diverse conditions. Second, in the Business to Engineering condition, we see a major difference (slower completions) across all rounds vs. the other three conditions. The Business recipient teams' performance also slows when they receive an Engineering source template, but this effect appears much less pronounced than in the Business to Engineering case.

Table 3.1: Descriptive Statistics across Conditions

Condition	Period	1	2	3	4	5
Business to Engineering	Mean	17.86	13.44	9.44	7.88	7.08
(FD_{BE})	Std. Dev.	2.43	2.44	2.15	1.83	1.42
Business to Business	Mean	12.48	8.79	7.79	6.77	6.20
(Non-FD_{BB})	Std. Dev.	1.63	1.28	1.69	1.19	1.12
Engineering to Business	Mean	13.46	8.72	7.53	7.16	6.59
(FD_{EB})	Std. Dev.	1.19	1.06	0.69	0.56	0.52
Engineering to Engineering	Mean	12.89	8.18	7.16	6.49	6.05
(Non-FD_{EE})	Std. Dev.	1.28	0.84	0.99	0.71	0.57

Notes. Time is measured in minutes required to complete a product according to specifications.

To analyze our data more formally, we estimated a model that allowed us to differentiate learning curves across our experimental conditions. In accordance with H1A and H1B, we were especially interested in examining whether the parameters of the learning curve, i.e., the initial time to build the product (=*a*) and the learning rate (=*b*), changed across different experimental conditions. We used the standard power law of learning in our model and used natural logs to linearize the model. Further, our model needed to account for the differences in learning curves across teams. Because we only observed teams for a few periods, we captured different learning curves across teams through random slopes and intercepts. Our model specification was as follows:

$$\begin{aligned}\ln\left(t_{p(i)}\right) &= \ln\left(a_i\right) - b_i \ln\left(p\right) \\ &+ a_1 FD_i + a_2 TR_i + a_3 FD_i \times TR_i \\ &+ a_4 \ln\left(p\right) \times FD_i + a_5 \ln\left(p\right) \times TR_i + a_6 \ln\left(p\right) \times FD_i \times TR + \varepsilon_p\end{aligned}$$

In this specification, $t_{p(i)}$ refers to the duration of building the product for team *i* in period *p*. The constant a_i and the slope b_i are the parameters of the learning curve for team *i*, drawn from a multivariate normal distribution with standard deviations σ_a, σ_b and correlation coefficient ρ_{ab}. This aspect of our model allowed us to efficiently represent the data structure of multiple observations being nested in the same team while explicitly recognizing that the parameters of the learning curve of a team are likely correlated with each other so that longer initial task durations likely imply steeper learning curves. The dummy variables FD_i and TR_i (for Functional Diversity and Template Recipient) capture the experimental condition of team i and shift both the intercept and slope of the learning curve. When both FD and TR are turned on, that means the template originates from the Business teams and the Engineering teams are the recipients. Finally, deviations from the power law of learning are permitted through the random error term ε_p, which is distributed normally with time period specific standard deviation σ_p. This aspect of our model allowed us to capture heteroscedasticity in the data caused by later periods possibly exhibiting less noise than earlier periods. The model was estimated in Stata 14.2 using the "mixed" procedure. Results from the estimation are summarized in Table 3.2.

Table 3.2: Estimation Results from Random Effects Learning Curve Model

Variable	Coefficient	Std. Error
Func Div (Eng. to Bus.)	0.05	(0.04)
Temp. Recipient (Eng. to Eng.)	0.01	(0.04)
Func Div x Temp. Recipient (Bus. to Eng.)	0.34^{**}	(0.06)
ln(p)	-0.44^{**}	(0.02)
ln(p)xFunc Div (Eng. to Bus.)	-0.01	(0.03)
ln(p)xTemp. Recipient (Eng. to Eng.)	-0.03	(0.03)
ln(p)xFunc. Div. x Temp. Recipient (Bus. to Eng.)	-0.13^{**}	(0.05)
Constant	2.50^{**}	(0.03)
σ_a	0.06^{**}	(0.02)
σ_b	0.04^{**}	(0.01)
ρ_{ab}	0.99^{**}	(0.00)
σ_1	0.11^{**}	(0.01)
σ_2	0.14^{**}	(0.14)
σ_3	0.14^{**}	(0.01)
σ_4	0.10^{**}	(0.01)
σ_5	0.11^{**}	(0.01)
N	300 [60]	
χ^2	1744.36^{**}	

Notes. $^{**}p\leq0.01$; $^{*}p\leq0.05$; N refers to the number of observations, with the number of teams in brackets.

From these results, several findings emerge. First, the direct treatment effect of functional diversity when the recipient is Engineering is significant and positive. This means that the initial time to build the product was longer when the Engineering teams received a template from the Business source. This provides mixed support for Hypothesis 1, because contrary to the results above, when Business students received knowledge from Engineering students, they performed in line with the teams of Business students that received the template from Business students. Within the FD_{BE} experiments, there was a clear disregard by the Engineering recipient teams for the information that was available to them from the Business source. Second, the results show that while the initial performance within the FD_{BE} condition lags the other treatments, there is also faster learning throughout the rest of the experiment. This finding is somewhat moot though, since throughout the experiment there remains a sizable performance deficit versus the other three conditions, ranging from 10% to 40%. These results corroborate past research (Dougherty, 1992; Ancona and Caldwell, 1992) that demonstrates the difficulty functionally diverse teams have with sharing thoughts and effectively completing tasks, at least when the recipients were Engineering students. Interestingly, when the Business teams were receiving knowledge from the Engineering source, they reviewed it thoroughly and used the information, allowing them to get off to a good start. Perhaps this was because many of them saw this as an engineering task. Also, Business school students are asked to work across functional interests on a regular basis in classes, so being asked to work with knowledge received from engineers was not an unusual request.

Hypothesis 2 argues that task and process conflict will be higher within the functionally diverse conditions.

Table 3.3: Self-Reported Changes

(between rounds)	**Period**	**1-2**	**2-3**	**3-4**	**4-5**
Functional Diversity	mean	2.13	1.57	0.83	0.57
Non-Functional Diversity	mean	1.27	0.73	0.67	0.43
	p-value	≤0.01	≤0.01	0.41	0.53

Notes. Changes made between rounds were self-reported by production teams and validated by two Ph.D. students.

The time between each round was given so that teams could review their operational strategy and make changes if necessary. Driven by the desire to achieve the highest financial compensation possible, it was in each team's best interest to ensure a winning strategy was in place. After tallying the number of ideas per round and comparing teams within each treatment, a clear pattern emerges. First, teams within the functionally diverse condition search far more than those in the non-functionally diverse conditions, especially in the first two rounds (see Table 3.3, with data aggregated to Functional Diversity vs. Non Functional Diversity because patterns were similar). A t-test between FD vs. non-FD search activity exhibits a p-value of .005 between round 1 and 2 and .001 between round 2 and 3. In rounds 3-4 and 4-5, the amount of changes was statistically the same between the two conditions. These findings are consistent with the performance results from tables 1 & 2 because it shows that FD teams are not satisfied with the process they inherit so they make significantly more changes to their process in an effort to adapt it and improve. Conversely, those teams that received a template from their functional counterparts, followed their instructions from the onset, and largely kept the process in tact over time, which led to better performance overall. Therefore, Hypothesis 2 is confirmed. Additionally, this data serves as further evidence that using a proven template provides an operational advantage because it allows workers to focus on execution vs. focusing on both knowledge creation and execution.

3.5. Discussion

The question guiding this study has been "Does functional diversity impact the effectiveness of a proven template when transferring production process knowledge?" This is a compelling question because as work is routinely being done across functional lines within today's firms, it is important to know if that is the right approach, especially as it relates to the transfer of knowledge between multiple facilities. While there are other factors that could impact a firm's ability to effectively transfer process knowledge, this paper demonstrates that executing work between functions can not only lead to a much slower start up in the recipient location, in certain contexts, but also increased levels of task and process conflict. Since production moves usually entail the movement of current business, firms cannot afford to have slow start-ups and high levels of conflict if they want to meet obligations to their supply chain/business partners. This implies that when management is organizing their transfer team, a good structure would be to have several "source-recipient" dyads, like what FEM eventually did during their move into Thailand. One dyad that is comprised of all key functions that are involved in the move, including Engineering, Manufacturing, Finance, Planning, Sourcing, Product Development, etc. This team can address and track progress across all elements (both key and trivial) of the process move. There should also be function specific dyads that are not functionally diverse, with its sole focus on the elements of the move that are important to that function (e.g. Mfg. to Mfg.; Supply Planning to Supply Planning, etc.). This will ensure that the function specific knowledge of the production process is transferred properly, while also leveraging the collective creativity and knowledge of multiple functions.

In chapter 4, I investigate the role of *National Culture.* This factor is important to study because many of the production moves are happening between countries and therefore between cultures. I motivate the topic with a case example from ChiPak, who are going through a move from Asia (eastern hemisphere) to the Caribbean (western hemisphere) and have had some difficulty doing so. The topic of national culture builds well on chapter 3s discussion of functional diversity because in some past literature, *collocation*, which is similar to functional diversity, is seen as a way to mitigate the effects of culture changes. Therefore, I also investigate collocation and its impact on performance within and between cultures.

Chapter 4:

National Culture and its Impact on Knowledge Transfer Effectiveness

4.1 Introduction

Customers, competitors, investors and other stakeholders often pressure firms to shift production to alternative locations within and between countries. This pressure is usually due to a desire to reduce costs, expand current business, increase service capability, etc. Firms can be tempted to focus on the post-move value, discounting the effort it takes to execute a successful move. Moving a process is not a trivial exercise, and requires the firm to manage several strategic decisions, such as the location of new facility, brownfield vs. greenfield site (Gaimon et al. 2017), old vs. new equipment, etc. Perhaps the most important aspect of planning a move is how to effectively transfer the *knowledge* associated with the existing process. Knowledge transfer is important because the ability to share knowledge between units is a competitive advantage for firms (Argote and Ingram, 2000). Effectively managing knowledge transfer is challenging because knowledge is stored in members, tools and tasks (Argote 2013). Frequently, knowledge is not stored in an explicit manner, but is stored in a tacit form (Nonaka 1994).

Consider the example of ChiPak[9], a $100 million/yr. contract manufacturer based in China. ChiPak has been making parts and finished home goods since the 1970sin China. However, as production costs in China continued to rise between 2006-2014, the pressure from their large U.S. based customers pushed ChiPak to consider establishing a production presence in the Western hemisphere. After an exhaustive study, ChiPak chose a location in the Caribbean, due to the attractive labor costs, tax advantages and its

[9] We use the name "ChiPak" to conceal the actual identity of this company. We generally refer to their new location as "Caribbean" for confidentiality purposes as well.

proximity to customer facilities. They made a commitment to their customers to move at least 50% of their current production within 12 months. While most elements of the move (building acquisition, equipment installation) went well, ChiPak struggled to hire people who could match the level of skill, work ethic and performance of their Chinese workers. Often times during the interviewing process, Chipak would uncover a misalignment of expectations regarding the breadth and depth of worker responsibilities, including amount of work per person and product quality expectations. When they did find people whose work expectations were aligned with the company, many of them would quit during training because the process was long and arduous. Due to these difficulties, ChiPak had to adjust its scheduled move, extending the time horizon for a 50% move to ***two*** years, instead of one. In retrospect, ChiPak underestimated the cultural differences they would encounter when moving away from China to a location where skill level, work standards, norms and values are different.

As this example highlights, a production move can be even more challenging when a firm moves from one culture to another. However, many moves happen between cultures. For example, Ford announced in 2016 that they would be moving all small car production (e.g. Ford Focus) from the US to Mexico, due to lower production costs. In 2015, GE announced a plan to move final production of aero-derivatives turbines from the US to France, Hungary and China, to take advantage of available export financing in Europe. In 2014, Honeywell moved the production of electronic industrial control units from the US to Mexico, laying off over 100 workers in Pennsylvania.

In this study, we focus on two countries, United States and China, who are at the center of the globalization discussion and have very distinct cultures when compared to one another: Multiple studies (Chen et al 2015; Cohen et al. 2016; Sirkin et al. 2014) have offered evidence showing a great deal of production movement between the two countries in both directions. So we want to understand if the differences between these two cultures specifically impact manufacturing performance after a production move. Ultimately, our goal is to inform managerial strategy on how to manage a production move effectively between two countries that have unique cultures that are very different from each other. Therefore, the questions that guide our research are: <u>Does national culture matter when moving a production process from one culture to another</u>? <u>If national culture matters, what strategies can managers use to counter these effects</u>? We investigate these questions via a series of in-depth, cross-cultural behavioral experiments that took place in the U.S. and in China.

The following section examines relevant literature, theory and the hypotheses. Section 3 details our experimental design and the analysis of results. Lastly, we highlight the strategic and operational implications of the study, its limitations and explore future research directions.

4.2. Theory and Hypotheses

<u>Culture and its Impact on the Organization and on Operations</u>

With the expansion of globalization over the last few decades, national culture and its impact on organizations has become an important research topic. Hofstede describes national culture as "the collective programming of the mind, distinguishing one group or category of people from others" (Hofstede et al. 2010). Hofstede's 1980 study has formed the foundation for how researchers have approached the study of culture and management in general (Flynn and Saladin 2006). Hofstede (1980) uses data gathered from IBM employees across 70 countries from 1967-1973. From this extensive data collection, Hofstede developed several cultural dimensions and discussed how the various countries differ on each. He initially proposed four dimensions: ***individualism/collectivism***, ***power distance***, ***masculinity/femininity***, ***and uncertainty avoidance,*** and has since added two more: ***long term orientation and indulgence.***

<u>Individualism</u> can be described as a social pattern that consists of loosely linked individuals who view themselves as independent of collectives and who are motivated by their own preferences, needs, rights and contracts. Conversely, *<u>collectivism</u>* can be described as a social pattern that consists of closely linked individuals who see themselves as belonging to one or more collectives (e.g. family, coworkers, in-groups, organizations) and who are motivated by norms, duties, and obligations which are imposed by the collectives. *<u>Power distance</u>* can be defined as the extent to which the less

powerful members of institutions and organizations within a country accept that power is distributed unequally. *Masculinity* can be defined as having a preference for achievement, heroism, and material rewards for success. Conversely, *femininity* describes having a preference for cooperation, modesty, and quality of life. *Uncertainty avoidance* is the degree to which people in the society feel uncomfortable with uncertainty and ambiguity. *Long-term orientation* is defined as fostering of pragmatic virtues oriented toward future rewards, in particular perseverance, thrift, and adapting to changing circumstances. Lastly, *indulgence* is when a society allows relatively free gratification of basic and natural human desires related to enjoying life and having fun (Hofstede et al. 2010, pg. 519-522).

While national culture may have an impact on the entire organization, it is important that we understand its impact on Operations in particular. There are several studies that help develop our intuition as well as show how culture can influence operational performance. Flynn and Saladin (2006) sought to understand the role of national culture when implementing quality management programs. Armed with plant data from the World Class Manufacturing (WCM) project, they used the Malcolm Baldrige quality award framework and Hofstede's national culture dimensions to test correlations between the two. They find that national culture dimensions (Power Distance, Uncertainty Avoidance, Individualism, Masculinity) are related to performance. Ultimately, their analysis shows that there "is not a universal model for performance excellence and that practices and approaches should be adapted to the local culture" (Flynn and Saladin 2006, pg. 599).

Pagell et al. (2005) sought to test the validity of national culture as an explanatory variable for global operations decision-making. Essentially, they wanted to understand "why might resident managers based in different countries pursue significantly different approaches when faced with the same set of decisional factors (page 374)?" Using data collected for the Global Manufacturing Research Group (GMRG), as well as Hofstede's culture framework, they analyze sourcing, sales and forecasting decisions that are made across multiple countries and cultures. They present evidence across each decision area that shows how national culture drove variation in the differences between countries, confirming the author's initial hypothesis. . They also find that culture is not one-dimensional; countries may differ on one element of culture but not all.

Naor et al. (2010) investigate if *organizational* culture differs across countries. They also examine and how this concept relates to *national* culture. The paper also studies the congruence between organizational and national culture, and they examine how these two concepts affect manufacturing performance (cost, quality, delivery and flexibility). The authors argue that the interplay between both concepts is important, because if, for example, best practices or templates are shared globally, there may be cultural conflicts in certain locations. Using the 9 dimensions within the GLOBE national culture framework, along with data collected via the high-performance manufacturing (HPM) project, they find that national culture is related to manufacturing performance across all dimensions of the Globe framework.

Gray and Massimino (2014) seeks to understand if language and national cultural differences between a firm's headquarters and its manufacturing operation impact the operation's process compliance. Process compliance is defined as the "adherence to operational routines such as standard operation procedures, good manufacturing practices (GMPs), and governmental regulations" (pg. 1042). Using the sender-receiver model framework (Noorderhaven and Harzing 2009) as well as Hofstede's national culture dimensions, the authors use pharmaceutical industry FDA inspection data and find mixed results when testing for a link between national culture and process compliance. For two of the culture dimensions (power distance and uncertainty avoidance) they found a link to process compliance, but for long term orientation and individualism, there was no congruence.

In Ozer et al. 2014, the authors were interested in better understanding how dealing with partners within and across different cultures impacts trust, trustworthiness and information sharing within a supply chain. They created a repeated interaction experimental design that included subjects from culturally heterogeneous locations - one culture being collectivist (China) and the other culture being individualistic (U.S.A.). This design was unique and perhaps the only behavioral operations experiment between two countries until the current study. Within the experiment, there was a two-tier supply chain where one subject is the supplier and the other subject is the retailer that is providing forecast information to the supplier. The authors provide several key findings. First, on average, Chinese retailers inflate forecast information twice as much as U.S. retailers do. Chinese suppliers also rely less on the retailer's forecast when determining the production quantity. This lack of trust can lead to a 10% loss in supply chain profit and efficiency. The authors partially attribute this lack of trust from the Chinese on their national culture and institutional environment. Specifically, they posit that the collectivist orientation within Chinese culture restricts trust and trustworthiness "within one's tight social network", which formed due to family ties or a long-term relationship. Second, their analysis of within-country and cross-country supply chains shows that both the Chinese and U.S. individuals trust U.S. partners more than Chinese ones.

National Culture and Knowledge Management

National culture and its impact on knowledge management has been studied previously. Although previous papers do not address the topic in the same manner as the current study, there are several studies helpful in framing our theory and related hypotheses.

Bhagat et al. (2002) generates theory regarding how information can be transferred effectively across country borders between organizations with different cultural backgrounds. Borrowing largely from De Long and Fahey (2000), Garud and Nayyar (1994) and Hofstede, they create a conceptual model where they analyze three types of knowledge: *human, social and structured.* Human knowledge involves what individuals know or know how to do. Social knowledge exists in relationships among individuals or within groups and is largely tacit since it consists of cultural norms that are generated by working together. Structured knowledge is embedded in organizational systems, processes, rules and routines and is largely explicit (pg. 206-207). They use these types of knowledge, coupled with various dimensions of knowledge to make propositions about how individualist (e.g. U.S.) and collectivist (e.g. China) cultures may differ in regards to knowledge transfer effectiveness. They argue, for example, that individualist cultures value explicit knowledge over tacit, whereas collectivists ones value tacit over explicit knowledge. Thus, transferring knowledge between dissimilar cultures will lead to reduced transfer effectiveness. Also, organizations located in individualist cultures are better able to transfer and absorb knowledge that is more explicit and independent, meaning it does not have to be described in relation to a larger body of knowledge. Lastly, they propose that individualist cultures may have difficulty transferring knowledge to collectivist ones, who may place more emphasis on collective goals and who are more relational.

Javidan et. al. (2005) discuss the case of NORDED, a Nordic European business school who established a training agreement with Tai Bank to train a number of Tai's middle and upper-middle managers for one year on *leadership* and *management of change*. Tai wanted quality advice from a reputable Western organization, but also wanted to ensure that their culture was not ignored while being trained. The program started well, but as the training went on frustration mounted within the Tai employees as they had difficulty implementing what they learned from NORDED into their local environment. NORDED instructors soon realized that what they were teaching clashed with the Tai Bank culture, where there is communication and information flow is vertical and there is a clear hierarchy that must be followed. NORDED believed that this style stifled the creativity and growth of middle managers as these managers had very little decision authority. This article also introduces the GLOBE study, which is seen as another substantive piece of culture research, along with Hofstede's work. There are nine dimensions and the authors discuss these dimensions in general, as well as in the context of the NORDED/Tai Bank case study. The authors conclude that knowledge transfer by itself poses challenges, so when the prospect of moving knowledge across cultures is introduced, it can pose additional issues. Executives should take a "proactive and systematic approach to dealing with cultural differences".

With this literature in mind, we believe there may be particular challenges when knowledge is passed from U.S. to China and from China to the U.S. We also believe that U.S. based teams will be more receptive to a template, and therefore will perform the task at a higher level than the Chinese based teams.

Hypothesis 1A: *Transferring production knowledge between dissimilar cultures will lead to reduced performance vs. transferring knowledge between similar cultures.*

Hypothesis 1B: *Transferring production knowledge between a U.S. based source and recipient dyads will lead to better performance vs. transferring knowledge between Chinese based source and recipient dyads, when colocation is not present.*

Co-location

With globalization more prevalent than ever, it is common to have employees with unique expertise, in different geographies, working on the same projects. This physical distance "decreases the probability that individuals meet by chance in hallways, at lunch, in front of closed elevators, or around the coffee machine. Distance hence decreases the chance of unplanned, serendipitous information transfer, and problem clarification" (Van den Bult and Moenaert 1998, pgs. S1-S2). Therefore, it is important that organizations employ strategies that foster better collaboration and communication between these co-workers. While technology (e.g. video conferencing, instant messaging, email) has helped to close the gap that physical distance creates, many firms still see ***co-location***, or "bringing together personnel from different departments into the same location" (Kahn and McDonough 1997, pg. 162), as the most effective way to improve connectivity.

In fact, there is a solid track record of firms employing this strategy successfully. For over two decades, Ford has employed a co-location approach in five vehicle centers, where designers, engineers and other supply chain functions work together on common projects. Ford also found that the co-location of various engineering sub-teams led to the development of the Mustang (Peitrangelo, 1993). McDonnell-Douglas saw the successful integration of the engineering and production departments when co-location was employed (Bergstrom, 1991). Lastly, when Honda co-located their suppliers' engineers with Honda's engineering, design and production people, it led to a stronger supplier-customer relationship. Various researchers have found that colocation leads to improved communication and collaboration (Van den Bulte and Moenaert 1998; Kahn and McDonough 1997) and to higher manufacturing conformance quality (Gray et al. 2015).

In fact, Gray et al. (2015) finds that the positive impact that colocation has on manufacturing quality is enhanced further when deployed in plants with a high level of tacit process knowledge. The authors find that it is important for firms to match their organizational design with strategies that will deliver the expected outcomes, especially as it relates to quality.

Even though colocation has its advantages, there are also potential drawbacks. Kahn and McDonough (1997) finds that while colocation leads to improved collaboration between R&D and Manufacturing, it does not lead to improved performance. Also, colocation comes at a high cost. When firms like Apple, P&G, and Hewlett-Packard began to offshore their manufacturing to China in the 1990s/early 2000s, they mitigated their risk by collocating their U.S. technical staff in China for weeks at a time. In addition, they would periodically deploy other company personnel (e.g. Supply Planning, Purchasing, Finance, General Management) to China to ensure the business was running smoothly. The travel costs alone factored into the millions of dollars each year. Net, while there may be benefits to collocating personnel, companies may find it to be too costly or time-consuming, especially when it happens between countries (Kahn and McDonough 1997).

In addition to gaining a better understanding of how national culture impacts knowledge transfer effectiveness, we are interested in understanding if colocation plays a role in mitigating the effects that culture may present during knowledge transfer. In this study, we transfer knowledge within and between U.S. and China based teams and assess their ability to take the knowledge to perform a production related task. The primary vehicle of knowledge transfer is a process template, which is knowledge in an explicit form. Bhagat et al (2002) finds that collectivist cultures are less likely than individualists to emphasize the significance of information that is written and codified and are more likely than individualists to disregard such information. To that end, collectivist cultures value ***tacit*** knowledge more than ***explicit*** knowledge. With this in mind, we anticipate that when transferring knowledge to a collectivist culture, having a source representative collocated with the recipient teams may improve transfer effectiveness. Especially since past literature (Gray et al 2015) finds colocation to be more valuable when transferring tacit information. Conversely, introducing colocation when transferring to an individualist culture will not improve performance.

Hypothesis 2A: *Co-location will lead to better performance for Chinese recipient teams vs. when co-location is not present.*

Hypothesis 2B: *Co-location will not lead to better performance for U.S. based recipient teams vs. when co-location is not present.*

Power Distance and its Impact on Search and Conflict

We are also interested in understanding if there will be a difference between cultures in its desire to make changes to the production process that has been transferred into its facilities. Change is important because no company operates in a static environment and many companies regard a process move as an opportunity to change the product or process itself.

If we look at Hofstede's research to develop intuition regarding which cultural dimension(s) may apply to a cultures desire to make/not make changes, we focus on one: *Power Distance*. This dimension is defined as: "the extent to which the less powerful members of institutions and organizations within a country accept that power is distributed unequally" (Hofstede et al. 2010, pg. 61). In China, power distance is high; the subordinate-superior relationship tends to be polarized and there is no defense against power abuse by superiors. People are influenced by formal authority and believe that one should not aspire beyond their rank (Hofstede et al. 2010). With this in mind, a Chinese participant may be more resistant to change the process given to them, as they may see the template as a form of authority providing strict guidance. Conversely, in the U.S., power distance is low, which is not surprising when you consider the emphasis on equal rights in all aspects of American society. In U.S. organizations, "hierarchy is established for convenience, superiors are accessible and managers rely on individual employees and teams for their expertise" (Hofstede.com). Between managers and those who report to them, "communication is informal, direct and participative to a degree" (Hofstede.com).

Jehn et al. 1999 states that when teams disagree on "what to do" within a task assignment, that is *task* conflict. When they disagree on "how to do it" within a task assignment, that is *process* conflict. We argue that teams from a culture that is low in Power Distance, like the U.S., will seek to make more changes to the process they are inheriting. Whereas, the teams from a culture that has a high level of Power Distance, like China, will not seek to cause conflict by making changes. In our experiment, we track the changes made by each team and aggregate it by culture in table 4.4. We use these changes[10] as a proxy for conflict because it shows that teams are not content with doing what has been given to them, so they are searching for an optimized solution via changes to the process. In past literature, researchers (Rivkin and Siggelkow 2003; Siggelkow and Rivkin 2005, etc.) discuss *search* as a way to describe how firms must look for a combination of design choices that will lead to the best possible performance. We expect the U.S. recipients to play a more active role in shaping their work when they receive a production process. Even if there is a prescriptive template, they feel empowered to communicate and express themselves. With this in mind, we present our final hypothesis:

Hypothesis 3: *Due to the differences in Power Distance, task and process conflict will be higher within U.S. recipient teams than within Chinese recipient teams.*

4.3 Experimental Design

Operationalizing a Production Process, National Culture and Co-location

In this study, we use Lego building sets to simulate a production process. Within rigorous academic research, there is a long history of using Legos. In Ariely et al. (2008), the authors, via a Lego building exercise, showed that when subjects could see their finished work accumulate versus it being disassembled over time, they were far more productive. Staats et al. (2012) used Legos to study the effects of adding people to project teams. They found that managers often focus on the advantages of additional manpower

[10] The number of unique ideas generated between each round was tracked. These ideas were self-reported by each participating team and independently validated by two PhD. candidates.

and underestimate the disadvantages, including coordination difficulties. Moreau and Engeset (2016) assigned subjects a well-defined task – a Lego kit with step-by-step instructions — as well as an ill-defined task – a bag of Lego bricks and pieces. They find that those who were initially given a well-defined task were not equipped to effectively manage an ill-defined task that required creativity later. Lastly, Kent and Siemsen (2017) leverage Lego building sets to study the impact of using templates when transferring production knowledge during a production process move. They find that template use drives better performance at the recipient site. However, they also find that strictly enforcing the template erodes performance; so the recipients must be allowed to make changes.

In our study of national culture, we focus on two countries that are not only at the center of the globalization and production move discussion, but who also represent very unique cultures. With many companies choosing to move their production from the U.S. to China, or China to the U.S. (Chen et al. 2015; Cohen et al. 2016), we want to understand if their cultural differences impact how knowledge is transferred. To represent the two countries, we recruited 320 students: 160 students from a large university in Midwestern United States and 160 students from a large university in Mainland China. We divided each group into 40 teams of 4 people, for a total of 80 teams (40 U.S. & 40 China). Since we are interested in understanding how ***national culture*** impacts knowledge transfer , we had a team of people in the U.S. and a team of people in China create a template based off the one used for the Lego Sunset Speeder (Lego No. 31017). These teams served as our "source" of knowledge within the experiment. This was done before we recruited the 320 experiment participants. Developing a template is key because even though each Lego building kit contains step-by-step instructions on how to build the product, there is no guidance given regarding the most efficient way to build it. Since the device has 32 steps and over 100 parts, the template is designed to deliver an optimal workflow that considers division of labor, material flow and the physical arrangement of the workers.

As previously mentioned, we are also interested in the impact *colocation* has on knowledge transfer, especially as it relates to mitigating the potentially negative effects of national culture. The way we operationalize colocation in our experiments is by having a member of the source team for the template (either U.S. or China), sit in with recipient teams to help guide them through their entire session. The collocated person does not help to build the device, but gives advice on how to not only interpret the template but he/she also suggests changes that can be made between rounds to improve performance.

4.3.1 Methods

Each of the teams was assigned to build a Lego device as quickly as possible with no defects for five rounds. In each round, teams started with a bag filled with unsorted Lego pieces. There were 10 teams in each of the 8 treatments, or 80 teams total. Similar to past studies interested in learning effects (Epple et al. 1991; Darr et al. 1995, etc.), time acts as a proxy for cost in our experiment. Devices considered defective had to be reassembled to conform to specifications before a round counted as complete; as such, quality defects only appear in our analysis as time delays.

Our unit of analysis in this study was the four-person production team. We varied three factors in the experiment: ***Source***, ***Recipient*** and ***Colocation***. We implemented these three factors in a 2^3 full factorial between-subjects design, giving us 8 treatments. As such, each team knew only of the experimental group it was in.

Table 4.1: Experimental Treatments

Treatment	Source	Recipient	Colocation
1	US	US	No
2	US	US	Yes
3	US	China	No
4	US	China	Yes
5	China	China	No
6	China	China	Yes
7	China	US	No
8	China	US	Yes

All teams were given five minutes to discuss their approach before the start of the first round. They were also given three minutes between rounds to reassess their approach and adjust their process. Note that we allowed the teams within all conditions to make changes between rounds. In that sense, the template given to them only represents a starting point for all teams. This design choice was made to allow adaptation by all teams across all experimental conditions. Per hypothesis 3, we kept track of the number of changes made by each team, so that we could assess if power distance was a factor in the level of task and process conflict within each team.

All participants were guaranteed $5 for completing the experiment, and each member of a four-person team received the same compensation. In addition, teams had an incentive to deliver high performance because more money was possible based on a tiered compensation structure tied to completion time (see appendix for experiment instructions).

4.3.2 Analysis and Results

Even though teams in both countries had 5 minutes before the first round to understand their task and strategize, how they used this time was uniquely different. The U.S. teams usually spent more time reading the template and talking about what it meant, while the Chinese teams usually spent the majority of their time asking questions of the researcher. This trend was exacerbated in the colocation sessions, as the Chinese teams listened to and ask questions of the collocated member, while the U.S. teams still chose to focus on the written template as well as the team members who were actually going to build the device. Between rounds, the teams were given several minutes to talk about their performance and make changes if they desired. Again, there was a different approach taken in each country. In the U.S., the team members spent their time brainstorming changes they could make to the process. Conversely, the Chinese teams spent their time discussing their roles/responsibilities and talked about how they can do their template mandated jobs better. Table 4 shows the difference in changes made between teams in both countries. As you can see, the U.S. based teams searched more frequently, which by itself doesn't mean there will be better performance, but it may offer some clues.

Before sharing more detailed statistical analysis, it is useful to examine our data descriptively. Table 1 lists descriptive statistics across different time periods for all 8 experimental conditions.

Table 4.2: Average Times to Complete Product

Condition	Period	1	2	3	4	5
U.S. to U.S.	Mean	11.05	8.12	6.71	6.08	4.91
	Std. Dev.	1.00	1.98	1.68	0.87	0.53
0U.S. to U.S. (collocated)	Mean	12.13	8.41	7.21	6.09	5.21
	Std. Dev.	1.10	0.77	0.69	0.63	0.53
U.S. to China	Mean	16.56	11.25	8.53	7.20	6.07
	Std. Dev.	2.64	1.91	2.16	2.48	1.28
U.S. to China (collocated)	Mean	11.78	9.09	8.02	6.56	6.06
	Std. Dev.	1.18	0.40	1.15	1.40	1.39
China to China	Mean	18.13	10.36	8.95	6.53	7.11
	Std. Dev.	3.51	1.65	2.14	0.69	3.57
China to China (collocated)	Mean	11.58	8.05	6.72	5.93	5.38
	Std. Dev.	1.27	1.16	1.17	0.85	0.91
China to U.S.	Mean	13.41	8.70	6.99	5.91	5.74
	Std. Dev.	1.76	0.91	0.99	0.63	0.78
China to U.S. (collocated)	Mean	12.60	8.96	7.29	6.19	5.75
	Std. Dev.	1.55	1.23	1.09	0.87	0.88

Notes. Time is measured in minutes required to complete a product according to specifications.

There are several key takeaways from the descriptive data. First, the standard learning curve (i.e. time decreasing at a decreasing rate) is present across all the treatments. Second, colocation improved the performance of the Chinese teams. Not only was the impact of colocation noticeable for completion time, but it also reduced the variation between teams per round. Lastly, U.S. teams performed substantially better than Chinese, especially when colocation was not present. The average difference between US and China team performance per round is 13%.

To analyze our data more formally, we estimated a model that allowed us to differentiate learning curves across our experimental conditions. In accordance with H1 and H2, we were especially interested in examining whether the parameters of the learning curve, i.e., the initial time to build the product (=*a*) and the learning rate (=*b*), changed across different experimental conditions, specifically national culture and colocation. We applied the standard power law of learning in our model and used natural logs to linearize the model. Further, our model needed to account for the differences in learning curves across teams. Because we only observed teams for a few periods, we captured different learning curves across teams through random slopes and intercepts. Our model specification was as follows:

$$\ln (t_{p(i)}) = \ln (a_i) - b_i \ln(p) + S_{us}R_{us}C_{high i} \ (a_1 - b_1 \ln (p)) + S_{us}R_{cn}C_{high i} \ (a_2 - b_2 \ln (p) + S_{us}R_{cn}C_{low i} \ (a_3 - b_3 \ln (p)) + S_{cn}R_{cn}C_{high i} \ (a_4 - b_4 \ln (p)) + S_{cn}R_{cn}C_{low i} \ (a_5 - b_5 \ln (p)) + S_{cn}R_{us}C_{high i} \ (a_6 - b_6 \ln (p)) + S_{cn}R_{us}C_{low i} \ (a_7 - b_7 \ln (p)) + \varepsilon_p$$

In this specification, $t_{p(i)}$ refers to the duration of building the product for team *i* in period *p*. The constant a_i and the slope b_i are the parameters of the learning curve for team *i*, drawn from a multivariate normal distribution with standard deviations σ_a, σ_b and correlation coefficient ρ_{ab}. This aspect of our model allowed us to efficiently represent the data structure of multiple observations being nested in the same team while explicitly recognizing that the parameters of the learning curve of a team are likely correlated with each other so that longer initial task durations likely imply steeper learning curves. The dummy variables $S_{i,}$ R_i and C_i (for source, recipient and colocation) capture the experimental condition of team *i* and shift both the intercept and slope of the learning curve. Finally, deviations from the power law of learning are permitted through the random error term ε_p, which is distributed normally with period specific standard deviation σ_p. This aspect of our model allowed us to capture heteroscedasticity in the data caused by later periods possibly exhibiting less noise than earlier periods. The model was estimated in Stata 14.2 using the “mixed” procedure. Results from the estimation are summarized in Table 2.

Table 4.3 - Estimation Results from Random Effects Learning Curve Model

Variable	Coefficient	Std. Error
China to China	0.46^{**}	(0.06)
China to U.S.	0.18^{**}	(0.06)
U.S. to China	0.23^{**}	(0.08)
U.S. to U.S. x Colocation	0.09	(0.06)
China to China x Colocation	-0.52^{**}	(0.08)
China to U.S. x Colocation	-0.14	(0.08)
U.S. to China x Colocation	-0.23^{*}	(0.12)
ln(p)	-0.47^{**}	(0.04)
ln(p) x China to China	-0.20^{**}	(0.05)
ln(p) x China to US	$-0.10^{\dagger}$	(0.05)
ln(p) x U.S. to China	$0.14^{\dagger}$	(0.08)
ln(p) x U.S. to U.S. x Colocation	-0.04	(0.05)
ln(p) x China to China x Colocation	0.22^{**}	(0.08)
ln(p) x China to U.S. x Colocation	0.1	(0.80)
ln(p) x U.S. to China x Colocation	-0.08	(0.11)
Constant	2.40^{**}	(0.04)
σ_a	0.10^{**}	(0.02)
σ_b	0.08^{**}	(0.02)
ρ_{ab}	-0.36^{**}	(0.28)
σ_1	0.10^{**}	(0.02)
σ_2	0.12^{**}	(0.01)
σ_3	0.14^{**}	(0.01)
σ_4	0.10^{**}	(0.01)
σ_5	0.16^{**}	(0.02)
N	400 [80]	
χ^2	1680.39^{**}	

Notes. $^{**}p\leq0.01$; $^{*}p\leq0.05$; $^{\dagger}p\leq0.10$. N refers to the number of observations, with the number of teams in brackets.

There are several key findings from our analysis. H1A argues that the performance of cross-cultural teams will lag behind that of the within culture teams. This is confirmed, as the average intercept of the cross culture teams is higher, which means their initial completion times were significantly slower. H1B argues that the performance of the U.S. recipient teams will outpace that of the Chinese recipient teams when colocation is not present. This is also confirmed, since the times of the Chinese teams were much slower than the U.S. teams throughout the experiment. In both cases, the Cross Culture and Chinese teams have learning rates in line with the group we are comparing them to, however in the case of the Chinese vs. U.S. teams it is of little consequence, since the actual performance gap still remains throughout the experiment. The Chinese teams underperform the U.S. teams by an average of 25% each round when collocation is not present.

In H2A and H2B, we argue that colocation ***will*** matter for Chinese recipient teams but ***will not*** matter for U.S. teams. Both of these hypotheses were confirmed in resounding fashion. For the Chinese teams, colocation made a difference in not only how they started, but also how quickly they learned over time. Also, colocation served as a way to standardize performance, as the average standard deviations for both US to China collocated and China-to-China collocated were reduced (see Table 1). Conversely, the performance of U.S. teams was not improved and in fact when adding colocation to the U.S to U.S. knowledge transfer dyad, the performance was made worse. These results are consistent with what we observed in the experimental sessions, as the Chinese teams were eager to learn from someone who had previous experience. The U.S. teams, however, did not see the collocated person as value added since he/she was not helping to build the device.

In Hypothesis 3, we argue that due in part to the established Power Distance difference between China and the U.S. (Hofstede 1980), U.S. teams will be more willing to make changes (i.e. higher task and process conflict) to their inherited process than the Chinese. This is driven by the fact that Chinese teams will be hesitant to change the template they have been given, seeing them as “orders” vs. general guidance that can/should be improved upon. Understanding if one culture will be more willing to search/change is an important factor, because it has been established in past literature that firms that have a desire to search for ways to improve their design choices will perform better (Rivkin and Siggelkow, 2003; Siggelkow and Rivkin 2005). This hypothesis is also confirmed, as Table 4.4 shows a substantial difference in the self reported changes made by the U.S. vs. Chinese teams. It could also be argued that the U.S. teams' desire to make changes to their inherited process is one of the reasons why their performance in the experiment is better than the Chinese.

Table 4.4: Self-Reported Changes – U.S. vs. China

(between rounds)	**Period**	**1**	**2**	**3**	**4**
U.S. Recipient	mean	1.675	1.1	0.4	0.475
China Recipient	mean	0.25	0.3	0.125	0.075
	p-value	≤0.01	≤0.01	≤0.01	≤0.01

Notes. Changes made between rounds were self-reported by production teams and validated by two Ph.D. students.

4.4. Conclusion

Does national culture matter when moving production process knowledge from one culture to another? This is an important question because the increase of globalization is driving firms to move their production between countries to take advantage of lower production costs, tax advantages, customer access, etc. Movement is happening at a rapid pace and will continue to increase, especially as production costs in China increase, making them on par or higher than U.S. costs (BCG report, citation needed). And if national culture matters and the impact is negative, what strategies can be implemented to neutralize these effects? This is key because we not only want to diagnose potential issues that may arise during a move, but also prescribe solutions that will help firms reduce the effect of the issues and thereby drive project success. We investigated these questions through a series of in depth, cross-cultural behavioral experiments that took in place at universities in the U.S. and China.

We find that transferring production knowledge between cultures is more difficult than transferring within cultures, especially in the initial stages. The impact we saw would have been even more substantial if not for the difficulty Chinese recipient teams had in general with receiving explicit knowledge in the form of a template, even when it was from a Chinese source. This leads to our second finding, which is that U.S. teams performed better than Chinese teams with the explicit knowledge (template) that was transferred and while the learning rates over time between the two countries were similar, the U.S. teams still outpaced their Chinese counterparts in completion time by an average of 25% per round when colocation is not present, and 13% when it was. This result is consistent with past literature (Bhagat et al. 2002) that argues that individualist countries, like the U.S., find more value in *explicit* knowledge than collectivist countries (like China) do.

We investigated colocation as a strategy that can serve as a way to mitigate the negative cultural effects. Colocation, or the "bringing together of personnel from different departments into the same location" (Kahn and McDonough 1997, pg. 162), increases the amount of tacit knowledge being shared and this form of knowledge is what collectivist countries value more than explicit knowledge (Bhagat et. al. 2002). Within our experiment, colocation significantly impacted the performance of the Chinese, improving their initial performance and the learning rate over time.

Lastly, we wanted to understand if established cultural differences, like those presented by Hofstede (1980) would drive unique behaviors among the recipient teams as it relates to searching for ways to improve the process they inherited. Among the dimensions posited by Hofstede's research, we focus on *Power Distance,* which is the "extent to which less powerful members of institutions and organizations within a country accept that power is distributed unequally" (Hofstede 2010, pg. 61). For collectivist countries like China, power distance is high, for the U.S. it's low. We tracked the number of self reported changes made per team between rounds and find that the Chinese, even when they weren't performing well, would not change the process they inherited. Conversely, the U.S. teams changed their processes often, especially in the first two rounds, and this likely was a reason why their performance was better, in addition to the fact that explicit knowledge suits their cultural disposition.

Taken together, these results show that when moving production process knowledge between unique cultures, there must be consideration taken for the ways in which each culture best receives knowledge. There is no "one size fits all" strategy so a firm must craft a plan specific to the needs of the recipient facility, otherwise the results will likely delay the start up, thereby putting current and future business at risk; not to mention harming the reputation of the firm.

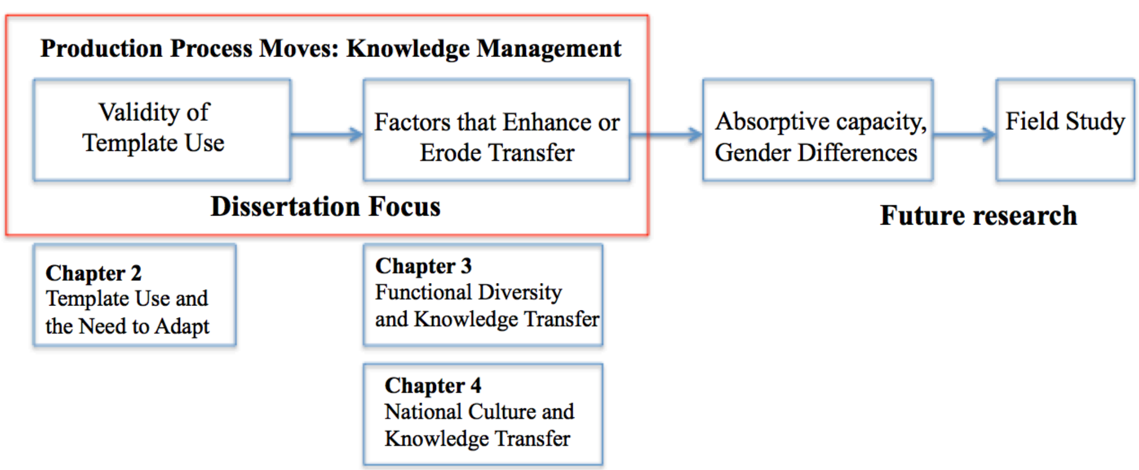
Chapter 5:

Conclusion

Production process moves have received minimal attention from scholars. While current research analyzes the *what*, *why* and *where* of production moves, the *how* remains relatively unexplored. Through discussions with multinational firms who have undergone both intercontinental and domestic moves over the last two decades, I identified several factors that may enhance or erode a firm's ability to transfer valuable yet elusive process knowledge. To better understand the link between these factors and performance, I created laboratory experiments to analyze cause and effect at a deep level. While there are other major factors that may impact a production move, like the greenfield vs. brownfield decision (Gaimon et al. 2017), this research makes a meaningful contribution to existing theory and has the potential to benefit practitioners.

This dissertation consisted of three chapters, with each chapter addressing a factor that may enhance or erode a firm's ability to transfer knowledge (Figure 5.1, repeated from Figure 1.1).

Figure 5.1 – Dissertation Structure



In chapter 2, I studied the link between template use and post move performance. Templates have long been thought of as an effective way to transfer knowledge, but it has also been shown to have limitations too. My research demonstrated that template use does lead to increased post move performance. Not only does the template allow teams to learn faster over time, but it also reduced the variability between teams. However, I also find that strict enforcement of the template crowds out empowerment and motivation among the recipient teams, leading to reduced performance. Therefore, firms engaged in moving production should create production templates to codify both critical and non-critical forms of knowledge, but should also leave some flexibility for the recipient to adapt the template to their unique skills, assets and environment. These findings serve as a solid foundation for the remainder of my dissertation, as I began to investigate factors that could enhance or erode the effectiveness of a proven template.

In chapter 3, I create a laboratory experiment that allows me to analyze the impact of between team functional diversity while transferring production knowledge. Having a diverse set of expertise and functional disciplines on the team is broadly thought of as the best approach when managing projects within the firm, but past literature has been divided, with some studies finding benefits while others find deficiencies with this approach. Within the experiment, production knowledge is transferred within and between unique functions, specifically subjects with a Business background vs. those with a background in Engineering. The results show that when knowledge is transferred from Business to Engineering, there is a performance reduction, likely due to a lack of credibility given to the Business teams by the Engineers. However, when knowledge is transferred from the Engineers to Business teams, performance is in line with the “within function” results. I also find that when knowledge is transferred between functions, there is an increase in both task (what to do) and process (how to do) conflict. Taken together, the results show that functional diversity does not work for all settings, and that managers should employ this approach carefully.

Finally, in chapter 4, I study the role that national culture plays in a firm’s ability to effectively transfer knowledge from a source to a recipient located in a different and unique culture. This topic is very timely, as most of the major moves over the last 20 years have taken place between countries, especially when many U.S. firms (Apple, P&G, Wal-Mart, IBM, H-P, etc.) in the late 1990s and early 2000s decided to take advantage of the low production costs in China. Also, over the last 5-7 years, firms are beginning to re-shore their production back to the U.S. or nearby due to the increasing production costs in China. To replicate these moves, I ran experiments in the U.S. and China with subjects who are born and raised in these unique cultures. These cultures are very different on several key cultural dimensions, including *individualism/collectivism* and *power distance*. These cultural dimensions are engrained into the fabric of these people, so it was interesting to study how these differences showed up in the knowledge transfer exercise. The results show that between culture knowledge transfer leads to reduced performance. I also find that knowledge transfer within culture from U.S. to U.S. leads to better performance than China to China. This result is consistent with the idea that individualist cultures (e.g. U.S.) find more value in explicit knowledge than collectivist cultures (e.g. China) do. However, I also find that a mitigating strategy for the difficulty the Chinese experience is by collocating someone from the source of the knowledge with the recipient teams while they are building their device. This change greatly increases both initial learning and learning over time, and it reduces variability between teams. Conversely, collocation shows no effect on the performance of U.S. teams. This finding is also consistent with the idea that collectivist cultures find more value in tacit knowledge than individualist cultures do. Lastly, I find that, perhaps due to the differences in *power distance,* the U.S. teams had much higher task and process conflict than the Chinese. However, this conflict may have also been a contributing factor in the U.S. team's ability to learn quicker than the Chinese as well.

To highlight the similarities and differences between each chapter, I provide an overview of the dissertation in table 5.1. While I use behavioral experiments for all three essays, I differentiate them by first establishing a foundation for effective knowledge transfer (i.e. template use) and then investigate two factors (functional diversity and national culture) that may enhance or erode knowledge transfer effectiveness. While there are other factors that impact production move performance, my dissertation delivers insights that advance our current understanding of how knowledge is created, transferred and retained. These insights will not only advance academic theory, but also inform the way firms create strategies when engaged in moves. I also hope that the novel approach I took to study production process moves (laboratory experiments) will inspire future researchers to also develop creative research methods to gather data and drive the field forward.

Table 5.1 Dissertation Summary

	Chapter #2	Chapter #3	Chapter #4
Tittle	Production Process Moves: Template Use and the Need to Adapt	Functional Diversity and its Impact on Knowledge Transfer Effectiveness	National Culture and its Impact on Knowledge Transfer Effectiveness
Unit of Analysis	Production Team	Production Team	Production Team
Data (Years)	Primary data (2015-2016)	Primary data (2016)	Primary data (2017)
Research Question(s)	* Does template use lead to higher performance when transferring production process knowledge? *Does rigidly enforcing a template result in adverse behavioral consequences at the recipient site?	*Does between team functional diversity impact the effectiveness of a proven template when transferring process knowledge?	*Does national culture matter when moving a production process from one culture to another? *If national culture matters, what strategies can be implemented to neutralize these effects?
Theoretical Lens	Standardization, Empowerment, Motivation, Organizational Search	Unique Thought Worlds, Homogenous Teams vs. Heterogeneous teams	Hofstede's Cultural Dimensions, Co-location
Research Method	Mixed Effects Regression model	Mixed Effects Regression model, T-Test	Mixed Effects Regression model, T-Test
Firm Implications	*Firms should create/use templates, but allow recipient facility to adjust.	*Functional Diversity can lead to reduced performance, so firms should use heterogeneous teams selectively.	*National culture matters, so firms should consider cultural differences when making productions move decisions. *Firms should use "colocation" selectively because it does not always improve performance.

Bibliography/References

Ancona, D., & Caldwell, D. (1992). Demography and Design: Predictors of New Product Team Performance. *Organization Science, 3*(3), 321-341. Retrieved from http://www.jstor.org/stable/2635276

Argote, L. 2013. *Organizational learning: Creating, retaining and transferring knowledge*. 2nd ed. Springer, New York.

Argote, L., D. Epple. 1990. Learning Curves in Manufacturing. *Science* **247**(4945) 920–924.

Argote, L., & Ingram, P. (2000). Knowledge Transfer: A Basis for Competitive Advantage in Firms. *Organizational Behavior and Human Decision Processes, 82*(1), 150-169.

Argote, L., B. McEvily, R. Reagans. 2003. Managing knowledge in organizations: An integrative framework and review of emerging themes. *Management Science* **49**(4) 571-582.

Argote, L., & Miron-Spektor, E. (2011). Organizational Learning: From Experience to Knowledge. *Organization Science : A Journal of the Institute of Management Sciences., 22*(5), 1123-1137.

Ariely, D., E. Kamenica, D. Prelec. 2008. Man's search for meaning: The case of Legos. *Journal of Economic Behavior & Organization* **67**(3) 671-677.

Bergstrom, R.P. The magic in small numbers (McDonnell Douglas project team). Production 70-72, 103 (May 1991).

Bernstein, E. 2012. The transparency paradox a role for privacy in organizational learning and operational control. *Administrative Science Quarterly* **57(**2) 181-216.

Bhagat, R. S., Kedia, B. L., Harveston, P. D., & Triandis, H. C. (2002). Cultural variations in the cross-border transfer of organizational knowledge: An integrative framework. *Academy of management review*, *27*(2), 204-221.

Boone, C., & Hendricks, W. (2009). Top management team diversity and firm performance: Moderators of functional-background and locus-of-control diversity. Management Science, 55, 165−180.

Bunderson, J., & Sutcliffe, K. (2002). Comparing Alternative Conceptualizations of Functional Diversity in Management Teams: Process and Performance Effects. *Academy of Management Journal., 45*(5), 875-893.

Cannon-Bowers, J., E. Salas, S. Converse. 1993. Shared mental models in expert team decision making. N. J. Castellan, Jr. ed. *Individual and Group Decision Making*. Lawrence Erlbaum, Hillsdale, NJ, 221-245.

Carrillo, J., C. Gaimon. 2000. Improving manufacturing performance through process change and knowledge creation. *Management Science* **46(**2) 265-288.

Chen, Y., M. Cohen, S. Cui, M. Dong, S. Liu, D. Simchi-Levi. 2015. Global Operations Sourcing Strategy: A Chinese Perspective. Working Paper, Available at SSRN: https://ssrn.com/abstract=2623770.

Cohen, W. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly.,* 128.

Cohen, M., S. Cui, E. Ricardo, A. Huchzermeier, P. Kouvelis, H. Lee, H. Matsuo, M. Steuber, A. Tsay. 2016. OM Forum - Benchmarking Global Production Sourcing Decisions: Where and Why Firms Offshore and Reshore. Working Paper, Stanford University Graduate School of Business Research Paper No. 16-28.

"Coming Home" *The Economist* 19 January 2013. https://www.economist.com/news/special-report/21569570-growing-number-american-companies-are-moving-their-manufacturing-back-united. Retrieved October 17, 2017.

Darr, E. D., L. Argote, D. Epple. 1995. The acquisition, transfer, and depreciation of knowledge in service organizations: Productivity in franchises. *Management Science* **41(**11) 1750-1762.

Darr, E., & Kurtzberg, T. (2000). An Investigation of Partner Similarity Dimensions on Knowledge Transfer. *Organizational Behavior and Human Decision Processes., 82*(1), 28-44.

David, W., & Fahey, L. (2000). Diagnosing cultural barriers to knowledge management. *The Academy of management executive*, *14*(4), 113-127.

de Holan, P. M., N. Phillips. 2004. Remembrance of Things Past? The Dynamics of Organizational Forgetting. *Management Science* **50(**11) 1603-1613.

Dougherty, D. 1992. Interpretive Barriers to Successful Product Innovation in Large Firms. *Organization Science* **3**(2) 179-202.

Ebbinghaus, H. 1885. *Über das Gedächtnis: Untersuchungen zur experimentellen Psychologie*. Duncker & Humblot.

Epple, D., L. Argote, R. Devadas. 1991. Organizational Learning Curves: A Method for Investigating Intra-Plant Transfer of Knowledge Acquired Through Learning By Doing. *Organization Science* **2**(1) 58-70.

Flynn, B. B., & Saladin, B. (2006). Relevance of Baldrige constructs in an international context: A study of national culture. *Journal of Operations Management*, *24*(5), 583-603.

Gaimon, C., G. F. Özkan, K. Napoleon. 2011. Dynamic resource capabilities: Managing workforce knowledge with a technology upgrade. *Organization Science* **22**(6) 1560-1578.

Gaimon, C., M. Hora, K. Ramachandran. 2017. *Process capabilities and leveraging advances in science and technology*. *Routledge's POM Companion Book.* Taylor & Francis Group, New York, NY. (Forthcoming).

Garud, R., & Nayyar, P. R. (1994). Transformative capacity: Continual structuring by intertemporal technology transfer. *Strategic management journal*, *15*(5), 365-385.

Geert, H., Jan, H. G., & M. Minkov (2010). Cultures and organizations: Software of the mind. *McGaw-Hill, London*.

Gioia, D. A., P. P. Poole. 1984. Scripts in organizational behavior. *Academy of Management Review* **9**(3): 449-459.

Gladstein, D. L. 1984. Groups in context: A model of task group effectiveness. *Administrative science quarterly* **29**(4) 499-517.

Gray, J. V., & Massimino, B. (2014). The effect of language differences and national culture on operational process compliance. *Production and Operations Management*, *23*(6), 1042-1056.

Gray, J. V., E. Siemsen, G. Vasudeva. 2015. Colocation still matters: Conformance quality and the interdependence of R&D and manufacturing in the pharmaceutical industry. *Management Science* **61**(11) 2760-2781.

Guzzo, R. A., M. W. Dickson. 1996. Teams in organizations: Recent research on performance and effectiveness. *Annual Review of Psychology* **47**(1) 307-338.

Heffner, T. S., J. E. Mathieu, G. F. Goodwin. 1995. An empirical investigation of mental models in team performance. JE Mathieu (Chair), Mental models and team effectiveness: Three empirical tests. Symposium conducted at the annual meeting of the Society for Industrial and Organizational Psychology, Orlando, FL.

Hofstede, G. (1980). Culture and organizations. *International Studies of Management & Organization*, *10*(4), 15-41.

Ichniowski, C., & Shaw, K. (1999). The Effects of Human Resource Management Systems on Economic Performance: An International Comparison of U.S. and Japanese Plants. *Management Science*, *45*(5), 704-721.

Jaikumar, R., R. Bohn. 1992. A dynamic approach to operations management: An alternative to static optimization. *International Journal of Production Economics* 27(3) 265-282.

Javidan, M., Stahl, G. K., Brodbeck, F., & Wilderom, C. P. (2005). Cross-border transfer of knowledge: Cultural lessons from Project GLOBE. *The Academy of Management Executive*, *19*(2), 59-76.

Jehn, K., Chadwick, C., & Thatcher, S. (1997). TO AGREE OR NOT TO AGREE: THE EFFECTS OF VALUE CONGRUENCE, INDIVIDUAL DEMOGRAPHIC DISSIMILARITY, AND CONFLICT ON WORKGROUP OUTCOMES. *International Journal of Conflict Management, 8*(4), 287-305.

Jehn, K. A., Northcraft, G. B., & Neale, M. A. (1999). Why Differences Make a Difference: A Field Study of Diversity, Conflict, and Performance in Workgroups. *Administrative Science Quarterly*, *44*(4), 741-763.

Jensen, R. J., G. Szulanski. 2007. Template use and the effectiveness of knowledge transfer. *Management Science* **53**(11) 1716-1730.

Jiang, J. J., G. Klein, H.-G. Hwang, J. Huang, S.-Y. Hung. 2004. An exploration of the relationship between software development process maturity and project performance. *Information & Management* **41**(3) 279-288.

Kahn, K. B., & McDonough, E. F. (1997). An empirical study of the relationships among co-location, integration, performance, and satisfaction. *Journal of Product Innovation Management*, *14*(3), 161-178.

Kent, P., & Siemsen, E. (2017). Production Process Moves: Template Use and the Need to Adapt. *Production and Operations Management,* Production and operations management, 2017.

Lapré, M. A., L. N. van Wassenhove. 2001. Creating and transferring knowledge for productivity improvement in factories. *Management Science* **47**(10) 1311-1325.

Mathieu, J. E., T. S. Heffner, G. F. Goodwin, E. Salas, J. A. Cannon-Bowers. 2000. The influence of shared mental models on team process and performance. *Journal of Applied Psychology* **85**(2) 273-283.

Mathieu, J. E., L. L. Gilson, T. M. Ruddy. 2006. Empowerment and team effectiveness: an empirical test of an integrated model. *Journal of Applied Psychology* **91**(1): 97-108.

McDonald, C. J. 1998. The evolution of Intel's Copy EXACTLY! technology transfer method. *Intel Technology Journal* 4(1) 1-6.

Moreau, C. P., M. G. Engeset. 2016. The Downstream Consequences of Problem-Solving Mindsets: How Playing with LEGO Influences Creativity. *Journal of Marketing Research* **53**(1) 18-30.

Naor, M., Linderman, K., & Schroeder, R. (2010). The globalization of operations in Eastern and Western countries: Unpacking the relationship between national and organizational culture and its impact on manufacturing performance. *Journal of operations management*, *28*(3), 194-205.

Nelson, R. R., G. S. Winter. 1982. *An Evolutionary Theory of Economic Change*. Harvard University Press, Cambridge, MA.

Nonaka, I. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Organization Science: A Journal of the Institute of Management Sciences., 5*(1), 14-37.

Noorderhaven, N., & Harzing, A. W. (2009). Knowledge-sharing and social interaction within MNEs. *Journal of International Business Studies*, *40*(5), 719-741.

Norton, M. I., D. Mochon, D. Ariely. 2011. The IKEA effect: When labor leads to love. *Journal of Consumer Psychology* **22**(3) 453-460.

Özer, Ö., Zheng, Y., & Ren, Y. (2014). Trust, trustworthiness, and information sharing in supply chains bridging China and the United States. *Management Science*, *60*(10), 2435-2460.

Özkan-Seely, G. F., C. Gaimon, S. Kavadias. 2015. Dynamic Knowledge Transfer and Knowledge Development for Product and Process Design Teams. *Manufacturing & Service Operations Management* **17**(2) 177-190.

Pagell, M., Katz, J. P., & Sheu, C. (2005). The importance of national culture in operations management research. *International Journal of Operations & Production Management*, *25*(4), 371-394.

Peitrangelo, J. Mustang Engineers slash cycle time. *Ward's Auto World* 29:71 (March 1993).

Pil, F. K., J. P. MacDuffie. 1999. Transferring competitive advantage across borders. A study of Japanese auto transplants in North America. Liker, J. K., W. M. Fruin, P. S. Adler. Eds. *Remade in America: Transplanting and Transforming Japanese Management Systems*. Oxford University Press, Oxford, UK., 39-74.

Reddy, W. B., A. Byrnes. 1972. Effects of interpersonal group composition on the problem-solving behavior of middle managers. *Journal of Applied Psychology* **56**(6) 516-517.

Rivkin, J. W., & Siggelkow, N. (2003). Balancing search and stability: Interdependencies among elements of organizational design. *Management Science*, *49*(3), 290-311.

Rouse, W. B., N. M. Morris. 1986. On looking into the black box: Prospects and limits in the search for mental models. *Psychological Bulletin* **100**(3) 349-363.

Sampson, R. C. (2007). R&D ALLIANCES AND FIRM PERFORMANCE: THE IMPACT OF TECHNOLOGICAL DIVERSITY AND ALLIANCE ORGANIZATION ON INNOVATION. *Academy Of Management Journal*, *50*(2), 364-386. doi:10.5465/AMJ.2007.24634443

Sampson, S. E., C. M. Froehle. 2006. Foundations and implications of a proposed unified services theory. *Production and Operations Management* **15**(2) 329-343.

Siemsen, E. 2011. The usefulness of behavioral laboratory experiments in supply chain management research. *Journal of Supply Chain Management* **47**(3) 17-18.

Siggelkow, N., & Rivkin, J. W. (2005). Speed and search: Designing organizations for turbulence and complexity. *Organization Science*, *16*(2), 101-122.

Sirkin, H. L., Zinser, M., & Rose, J. (2014). The Shifting Economics of Global Manufacturing: How Cost Competitiveness Is Changing Worldwide. *The Boston Consulting Group*.

Shalley, C. E., L. L. Gilson. 2016. Creativity and the management of technology: Balancing creativity and standardization. *Production and Operations Management* **26**(4) 605-616.

Sommer, S. C., C. H. Loch. 2004. Selectionism and learning in projects with complexity and unforeseeable uncertainty. *Management Science* **50**(10) 1334-1347.

Staats, B. R., K. L. Milkman, C. R. Fox. 2012. The team scaling fallacy: Underestimating the declining efficiency of larger teams. *Organizational Behavior and Human Decision Processes* **118**(2) 132-142.

Szulanski, G. 1996. Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strategic Management Journal*, 17(Winter) 27–43.

Szulanski, G. 2002. *Sticky Knowledge: Barriers to Knowing in the Firm*. Sage, London, UK.

Szulanski, G., R. J. Jensen. 2008. Growing through copying: The negative consequences of innovation on franchise network growth. *Research Policy* **37**(10) 1732-1741.

Terwiesch, C., Y. Xu. 2004. The copy-exactly ramp-up strategy: Trading-off learning with process change. *IEEE Transactions on Engineering Management* **51**(1) 70-84.

Thompson, P. 2007. How much did the Liberty shipbuilders forget? *Management Science* **53**(6): 908-918.

Thorndike, E. L. 1898. Animal intelligence: An experimental study of the associative processes in animals. *Psychological Review* **5**(5) 551-553.

Thurstone, L. L. 1919. The learning curve equation. *Psychological Monographs* 26(3) 1-51.

Van den Bulte, C., & Moenaert, R. K. (1998). The effects of R&D team co-location on communication patterns among R&D, marketing, and manufacturing. *Management Science*, *44*(11-part-2), S1-S18.

Van Der Vegt, G. S., & Bunderson, J. S. (2005). LEARNING AND PERFORMANCE IN MULTIDISCIPLINARY TEAMS: THE IMPORTANCE OF COLLECTIVE TEAM IDENTIFICATION. *Academy Of Management Journal*, *48*(3), 532-547. doi:10.5465/AMJ.2005.17407918

Venkatesh, V., H. Bala, T. A. Sykes. 2010. Impacts of Information and Communication Technology Implementations on Employees' Jobs in Service Organizations in India: A Multi□Method Longitudinal Field Study. *Production and Operations Management* **19**(5) 591-613.

Victorino, L., R. Verma, D. G. Wardell. 2013. Script usage in standardized and customized service encounters: Implications for perceived service quality. *Production and Operations Management* **22**(3) 518-534.

Volpe, C. E., J. A. Cannon-Bowers, E. Salas, P. E. Spector. 1996. The impact of cross-training on team functioning: An empirical investigation. *Human Factors* **38**(1) 87-100.

Von Hippel, E. 1994. 'Sticky information' and the locus of problem solving: Implications for innovation. *Management Science* **40**(4) 429-439.

Weber, R. A., C. F. Camerer. 2003. Cultural conflict and merger failure: An experimental approach. *Management Science* **49**(4) 400-415.

Winter, S. G., G. Szulanski. 2001. Replication as strategy. *Organization Science* **12**(6) 730-743.

Winter, S. G., G. Szulanski, D. Ringov, R. J. Jensen. 2012. Reproducing knowledge: Inaccurate replication and failure in franchise organizations. *Organization Science* **23**(3) 672-685.

Wright, T. P.. 1936. Learning curve. *Journal of the Aeronautical Sciences* 3(1) 122-128.

Zhang, X., K, M. Bartol. 2010. Linking empowering leadership and employee creativity: The influence of psychological empowerment, intrinsic motivation, and creative process engagement. *Academy of Management Journal* **53**(1) 107-128.

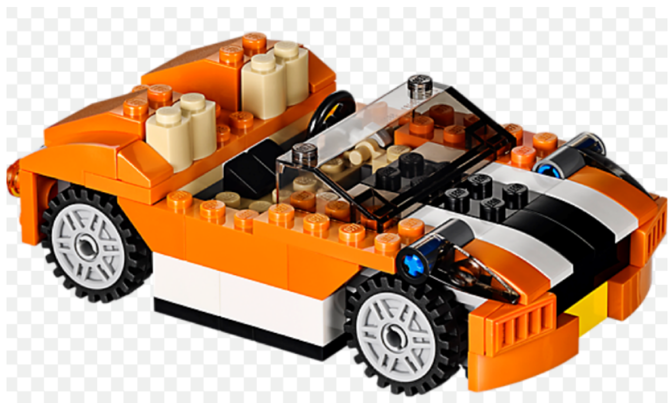
Zollo, M., & Reuer, J. (2010). Experience Spillovers Across Corporate Development Activities. *Organization Science: A Journal of the Institute of Management Sciences., 21*(6), 1195-1212.

Appendix A

Experiment Instructions for Chapter 2 study -

Instructions for Chapter 3 and 4 studies based off of the Chapter 2 "Template High/Change None – Sunset Speeder" instructions.

<u>Production Process Moves Experiment</u>
Template High/Change None - "Sunset Speeder" (4-person team)



Thank you for participating in our experiment:

- You will be engaged in building a Lego Sunset Speeder for 5 rounds, working together as a team.

- You have been assigned specific roles and responsibilities that you are expected to follow, even though you may begin to deviate from them after the first round (see below).

- Cost (completion time) and Quality (# of errors) are very important and will be tracked. Your objective is to build this device as quickly as possible with zero defects. Completion time will serve as a proxy for cost, so each round will be timed from start to finish. "Finish" will be when your team has submitted the device for final inspection and there are no defects/errors.

- In addition to your base pay, you can earn additional compensation each round if you are able to complete the device, **<u>without defects,</u>** in the following completion times:

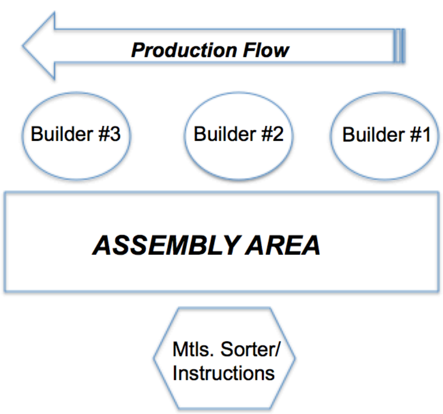
    - > 8 minutes = $1
    - 7 to 8 minutes = $2
    - 6 to 7 minutes = $3
    - 5 to 6 minutes = $4

- 4 to 5 minutes = \$5
- < 4 minutes = \$6

- Before you begin the first round, you will be given 5 minutes to discuss general strategy with one another. Each round ends when the team has fully assembled the device. Between rounds, your team will be given 3 minutes to strategize ways to improve your device building operation. If there are changes you want to make to the way you are organized, feel free to do so between rounds.

- When the 3-minute strategy session has been completed between rounds, each team will be notified and a new bag of device components will be placed on the table signifying the start of the next round. This will continue until the 5th round is completed.

Team members should sit in the following fashion while making this device:



Team Member Assignments

Position: Builder #1

- Responsible for steps 1-16 in Lego instructions.

- Position: Builder #2

- Responsible for steps 17-32 in Lego instructions, except for the 3 subassemblies in steps 20, 24 and 32.
- Will coordinate with Builder #3 to affix the subassemblies to the device at the appropriate time.

- Position: Builder #3

- Responsible for steps 20, 24 and 32, which are the subassemblies.
- Will coordinate work with Builder #2 to affix the subassemblies to the device at the appropriate time.

- The goal is to have the subassemblies completed by the time builder #2 begins building in step 17, therefore Builder #3 should start building subassemblies at the same time as Builder #1.

- Position: Material Sorter and Manager of Instructions

- Responsible to manage Lego instructions, working alongside each of the builders to ensure the device is built accurately.
- Responsible for sorting materials, helping each builder identify the correct parts to use to build the device. Need to avoid using the defective/wrong materials that can lead to finish product errors.

Production Process Moves Experiment
Template High/Change High: **"Red Go Kart"** (4-person team)

Thank you for participating in our experiment:

- You will be engaged in building a Lego Go-Kart for 5 rounds, working together as a team.

- You have been assigned specific roles and responsibilities that you are expected to follow, even though you may begin to deviate from them after the first round (see below).

- **Cost** (completion time) and **Quality** (# of errors) are very important and will be tracked. Your objective is to build this device as quickly as possible with zero defects. Completion time will serve as a proxy for cost, so each round will be timed from start to finish. "Finish" will be when your team has submitted the device for final inspection and there are no defects/errors.

- In addition to your base pay, you can earn additional compensation each round if you are able to complete the device, **without defects,** in the following completion times:

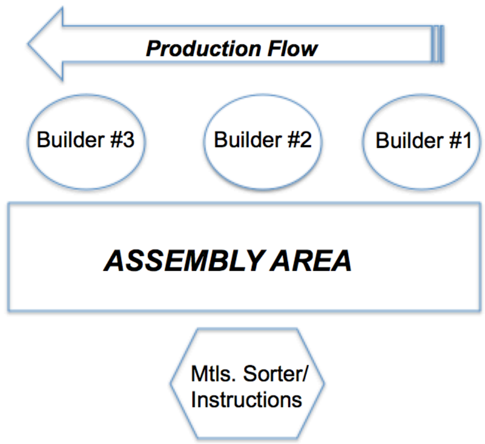
    - > 8 minutes = $1

- 7 to 8 minutes = $2
- 6 to 7 minutes = $3
- 5 to 6 minutes = $4
- 4 to 5 minutes = $5
- < 4 minutes = $6

- Before you begin the first round, you will be given 5 minutes to discuss general strategy with one another. Each round ends when the team has fully assembled the device. Between rounds, your team will be given 3 minutes to strategize ways to improve your device building operation. If there are changes you want to make to the way you are organized, feel free to do so between rounds.

- When the 3-minute strategy session has been completed between rounds, each team will be notified and a new bag of device components will be placed on the table signifying the start of the next round. This will continue until the 5th round is completed.

Team members should sit in the following fashion while making this device:



<u>Team Member Assignments</u>

<u>Position: Builder #1</u>

- Responsible for steps 1-13 in Lego instructions.

<u>Position: Builder #2</u>

- Responsible for steps 14-34 in Lego instructions, except for the 3 subassemblies in steps 28, 29 and 31.
- Will coordinate with Builder #3 to affix the subassemblies to the device at the appropriate time.

<u>Position: Builder #3</u>

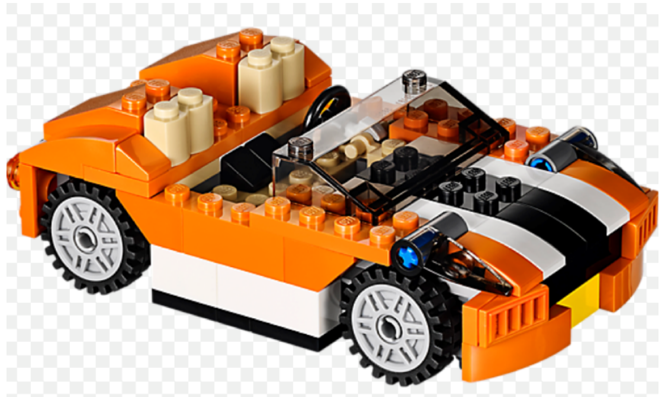
- Responsible for steps 28, 29 and 31, which are the subassemblies.
- Will coordinate work with Builder #2 to affix the subassemblies to the device at the appropriate time.
- The goal is to have the subassemblies completed by the time builder #2 begins building in step 14, therefore Builder #3 should start building subassemblies at the same time as Builder #1.

<u>Position: Material Sorter and Manager of Instructions</u>

- Responsible to manage Lego instructions, working alongside each of the builders to ensure the device is built accurately.
- Responsible for sorting materials, helping each builder identify the correct parts to use to build the device. Need to avoid using the defective/wrong materials that can lead to finish product errors.

<u>**Production Process Moves Experiment**</u>

No Template/Change None - "Sunset Speeder" (4-person team)



Thank you for participating in our experiments:

- You will build the Lego Sunset Speeder device 5 times, working together as a team.

- Cost (completion time) and Quality (# of errors) are very important and will be tracked. Your objective is to build this device as quickly as possible with zero defects. Completion time will serve as a proxy for cost, so each round will be timed from start to finish. "Finish" will be when your team has submitted the device for final inspection and there are no defects/errors.

- When building the device, your team may organize your operation however you like. To help facilitate this, you will be given 5 minutes before you begin the first round to organize.

- In addition to your base pay, you can earn additional compensation each round if you are able to complete the device, <u>**without defects,**</u> in the following times:

    - > 8 minutes = $1
    - 7 to 8 minutes = $2
    - 6 to 7 minutes = $3
    - 5 to 6 minutes = $4
    - 4 to 5 minutes = $5
    - < 4 minutes = $6

- Each round ends when the team has fully assembled the device. Between rounds, your team will be given 3 minutes to strategize ways to improve your operation. If there are changes you want to make to the way you are organized, feel free to do so between rounds.

- When the 3-minute strategy session has been completed between rounds, each team will be notified and a new bag of device components will be placed on the table signifying the start of the next round. This will continue until the 5th round is completed.

Production Process Moves Experiment
No Template/Change High: **"Red Go Kart"** (4-person team)

Thank you for participating in our experiments:

- You will build the Lego Go Kart device 5 times, working together as a team.

- Cost (completion time) and Quality (# of errors) are very important and will be tracked. Your objective is to build this device as quickly as possible with zero defects. Completion time will serve as a proxy for cost, so each round will be timed from start to finish. "Finish" will be when your team has submitted the device for final inspection and there are no defects/errors.

- When building the device, your team may organize your operation however you like. To help facilitate this, you will be given 5 minutes before you begin the first round to organize.

- In addition to your base pay, you can earn additional compensation each round if you are able to complete the device, **without defects,** in the following times:

    - > 8 minutes = $1
    - 7 to 8 minutes = $2
    - 6 to 7 minutes = $3
    - 5 to 6 minutes = $4
    - 4 to 5 minutes = $5
    - < 4 minutes = $6

- Each round ends when the team has fully assembled the device. Between rounds, your team will be given 3 minutes to strategize ways to improve your operation. If there are changes you want to make to the way you are organized, feel free to do so between rounds.

- When the 3-minute strategy session has been completed between rounds, each team will be notified and a new bag of device components will be placed on the table signifying the start of the next round. This will continue until the 5th round is completed.